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Effects of Macroeconomic Fundamentals and Crude Oil on Global Commodity Prices

Fernandez, Jose

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José Manuel Fernández

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ABSTRACT

This dissertation is composed of three empirical studies. The first study examines the long-run relationship between the real world price of maize, soybeans and sugar with the real world price of crude oil and a series of macroeconomic variables using a cointegration analysis from January 1982 until December 2012. The main empirical results support a strong causal relationship between maize and soybeans with crude oil, the real interest rate and the real U.S. exchange rate. It is shown that real world crude oil prices are cointegrated with real world prices of maize and soybeans for the entire sample period and that real oil prices have a one-to-one relationship with these commodities. In other words, a one-percent increase in the price of real crude oil is associated with a one-percent increase in the price of maize and soybeans. Moreover, we find that permanent shocks to crude oil prices are transmitted to both maize and soybeans by a factor of 0.67 in both cases. In addition, our results show that despite the instability associated with the period between 2007-2008, the cointegrating relationship between crude oil and these agricultural commodities has remained stable during the entire sample period. Finally, our results also suggest that although the real interest rate and the U.S. exchange rate are cointegrated with these commodities, it is only permanent shocks to real crude oil prices that have a permanent effect on the commodities price behavior.

In the second study I examine the degree of interdependence between three agricultural commodity prices, crude oil price returns, macroeconomic variables and the S&P GSCI commodity returns index. I apply Aielli [2013] cDCC model using monthly data from 1982 to 2012 to estimate the dynamic correlations of the returns series and endogenously detect any structural instability of the dynamic correlations. The results indicate that crude oil price returns present statistically significant dynamic correlations with all the macroeconomic variables in addition to the GSCI index. Additionally, we detect structural changes in these dynamic correlations mainly associated with the financial crisis of 2008. On the other hand, our results show that there exists no degree of interdependence between maize, soybeans and sugar with crude oil price returns and most of the macroeconomic variables. The exceptions are between soybeans with the U.S. exchange rate and sugar with global economic activity. Nevertheless, only the GSCI index presents significant dynamic correlations with these commodity price returns.

In the third study I apply an asset pricing theory model in order to evaluate the extent to which investment in futures commodity price indexes influence spot price return in a portfolio of commodity and energy prices. Particularly, we are interested in measuring the common risk factors of six agricultural commodities (e.g. maize, soybean, sugar, wheat, barley and sorghum) and global crude oil. Here, I aim to estimate their relationship with equities, the U.S. dollar, interest rates, a series of variables measuring the global macroeconomic performance and commodity futures price indexes. In contrast to the literature, instead of using a principal components analysis (PCA), which is concerned with explaining the return variances of a portfolio, I use a reduced rank approach in order to capture the canonical correlations in an effort to measure those factors which explain the risk to the commodity portfolio. This approach help us to understand the cross-section dependency of commodity markets with the global macroeconomic cycles as well as to capture the extent to which increasing portfolio investment by institutional investors, which has given rise to the so called "financialization of commodities", are motivated by diversification strategies or by speculative behavior in these markets. Our findings, indicate that even though macroeconomic factors, market specific and commodity futures indexes are captured among the risk factors in this commodity portfolio. Nevertheless, the factors associated with the market specific and the commodity futures indexes offer a hedge for the risks provided by the common macroeconomic factor. Therefore, using this approach, I conclude that commodity futures index investment appears to offer the diversification effect which has been the main driver of the so called commodity financialization within the past fifteen years.

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The road towards finishing this work has been a fruitful one with the support of many individuals and experiences alike. I have to thank my supervisor Bruce for his patience and support along way in these past three years. I also have to thank both my father and mother for the gift of life and the opportunity they have given me to enjoy it. I have to be grateful of my colleagues, friends, brother and sisters and rest of my family for their support and productive discussions, which has considerably improved my values and this work.

I thank my wife and her family which have all been supportive and understanding along this process. Thank you Canim for all your love and the grace you have brought to my life. You and you family have been a blessing in my life. Along side you, I have learned the values of family, love and forgiveness that has kept us bound. Thank you familia Çelebi for all your love and apple pies.

Leaving Cuba at age 14, arguably, was the best decision my family took. It was a crumbling society in disappear of hope that has not arrived 21 years later. I would not have been able to find and exploit my full potential under that amount of stress and injustices around me. Contradictory to my emotions, rationally, I have to be thankful that I left my homeland, even though that wound still is to be healed. Por ello mami, gracias por tomar la dificil decision y tener el valor de

sacarnos adelante en un pais tan dificil como Ecuador. Gracias por todos tus dias de trabajo para llevarnos un plato de comida a la mesa. Yo pienso en ello todos los dias de vida y trato de devolverlo con gestos como este. Gracias tambien papi por darnos el permiso de salida de Cuba y poner nuestro futuro delante de tus sentimientos personales. Sin esa decision hoy no hubiese podido escribir estas palabras. Gracias de todo corazon!

Sin dudas, la persona mas importante en vida es mi abuela Dulce Maria. Abue, no hay manera de comenzar a escribirte sin derramar lagrimas de anhelo que hubieses estado aqui conmigo como lo estuviste en mi graduacion del colegio. No hay manera de darte gracias por todo el amor que me diste, pero demonstrandote que valio la pena cada sacrificio y cada lagrima derramada en nuestro destierro. Tu me enseñaste el valor de ser agradecido con nuestra dicha y con aquellos que nos ayudan a crecer. En estas palabras trato de hacer honor a ello sin poder contener las ganas de abrazarte. No hay manera de devolverte tu amor ni tu esfuerzo. Gracias Abue!

Quisiera también dejar un mensaje de esperanza, valor y paz a mis compatriotas. Si bien es cierto que vivimos en un mundo que no ha sido escogido por nosotros, la realidad es que somos parte activa del mismo y por ello su futuro nos pertenece. No tememos la oportunidad de cambiar el pasado, pero el presente es guiado por acciones y desiciones cotidianas que influyen el mañana, nuestro futuro. El camino individual esta lleno de baches y cuchillos propios, pero en conjunto el camino comparte un mismo fin. A nivel individual, todos anhelamos un futuro con diferentes caracteristicas, pero en conjunto, ciertamente aspiramos a un presente mejor que el de ayer, y a un mañana diferente basado en el hoy ó quizás hasta basado en otro punto referencial. Es un proceso complejo no solo por su dinámica intertemporal, pero por su dimensión agregada. Yo, tanto como tu, quiero una Cuba más tolerable e inclusiva. Mi proposición es la siguiente: si como individuos podemos cesar de enfocarnos en las diferencias ideológicas y reconocer la fuerza y el beneficio social de trabajar en conjunto, ese día nuestra sociedad estará forjada en pilares que ningún individuo podrá desmoronar. El socialismo nos conducirá a lograr nuestros objetivos individuales y sociales, y no hablo del modelo económico, social y politico. Lo que propongo es un consenso tanto individual como social que nos permita convivir en armonía, así como considerar, respetar y valorar al individuo y sus derechos más esenciales. No es una tarea fácil, y su complejidad se deriva en que muchos de estos elementos son basados en derechos fundamentales que no son rígidos ni estáticos y es imperativo que abarquen el beneplácito social. Es por ello, que debemos construir estructuras universales basadas en la equidad individual, social y generacional, de tal manera que nos permita respetar nuestro pasado, así como también evolucionar y trascender las barreras idiológicas naturales del individuo.

Thank you all who have influenced my life one way or another and the ambitions keep on growing.

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CHAPTER 1

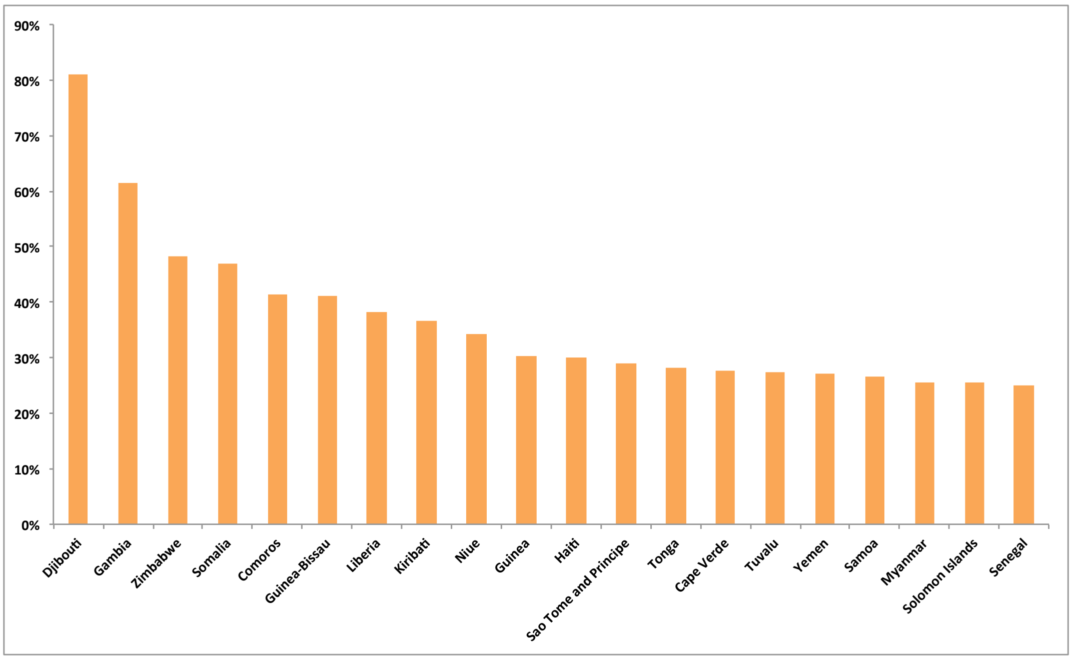
INTRODUCTION

In 2012, agriculture only accounted for approximately 3 percent of the world's GDP. Nevertheless, in a number of least developed countries (LCDs), agriculture contributed more than 25 percent of their total GDP [FAO, 2012a]. This suggests, events that increase uncertainty and volatility in the agricultural commodity market can cause serious economic disruptions as well as political unrest in these societies (For more details see: Bellemare [2011], Naylor and Falcon [2010] and von Braun [2008]). In addition, if one considers the following facts: (1) virtually all global current and future population growth is centred in LCDs countries [FAO, 2012a][1]; (2) by 2017 approximately 60 percent of the world's economic growth will be generated by emerging markets and developing economies [IMF, 2012]; (3) low income households in developing countries consume a significantly larger proportion of agricultural products than their wealthier counterparts [FAO, 2012c]. We can conclude that understanding the relationships and underlaying determinants of these cycles are of paramount interest, not just from the social and political perspectives, but also from the macroeconomic standpoint

[1]Economic growth in 2005 by middle and low income countries accounted for 41 percent of world GDP, measured in PPP international dollars, up from 32 percent in 1992 Alexandratos [2008].

considering that a great number of developing economies depend heavily on the exports and imports of these commodities (See Figures 1-1 and 1-2).

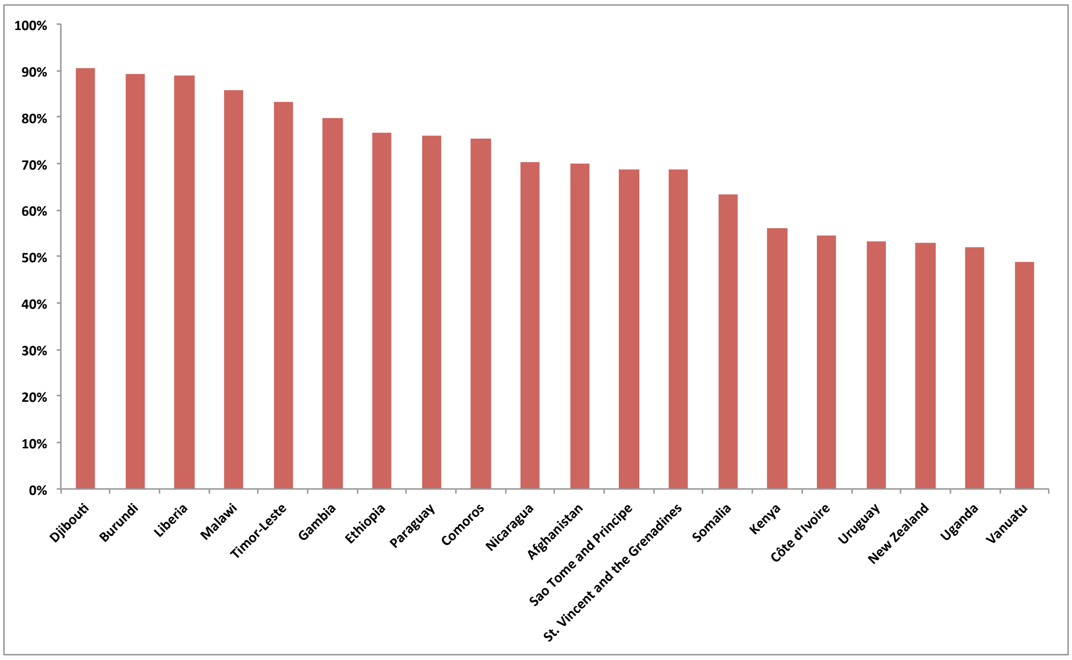
Figure 1-1: *Share on Total Agriculture Imports / Total Merchandise (Top 20 countries)*



Data Source: FAO [2012b]

Historically, not just agricultural commodities, but commodity prices in general have suffered from considerable price fluctuations. Although these fluctuations tend to disrupt the economic environment in all economies, raw commodity price shocks have less of an impact on developed countries since most of the food is heavily processed and these raw materials enter as a fraction of the price consumers end up paying [Carter et al., 2011]. A study by Gelos and Ustyugova [2012] concluded that "commodity price shocks have stronger effects on domestic inflation in developing than in advanced economies." On the other hand, energy price socks, such as the embargo imposed by the Organization of the Petroleum Exporting Countries (OPEC) in 1973, have had a substantial impact on the macroeconomic performance of developed economies. As a consequence, the study of energy shocks and its relationship with macroeconomic performance in developed economies has dominated the academic literature[2].

Figure 1-2: *Share on Total Agriculture Exports / Total Merchandise (Top 20 countries)*



Data Source: FAO [2012b]

The relationship between energy markets and agricultural commodity prices has always attracted the attention of policy makers and economists alike. Nevertheless, since the simultaneous energy and agricultural commodity price surge of 2006-08, many researchers have paid a closer attention to the relationship between these commodity groups. The main studies have concentrated in understanding the impact of biofuel production and demand on the dynamics of agricultural commodities and crude oil primarily [Helbling, 2012]. There exists a general un-

[2]For more details see Hamilton [2009] and Kilian [2009]

derstanding that as a consequence of the implementation of policies (primarily in the U.S., Europe and Brazil) to increase the production of biofuels (mainly ethanol and biodiesel), today agricultural commodities are competing with the same resources as energy commodities and consequently the relationship has become more susceptible to fluctuations in both markets.

Despite the increasing interests in studying the relationship between crude oil and commodity prices, currently there exists a number of aspects regarding this relationship that need to be explored. For example, there only exists a few studies that have attempted to study this relationship with a longer time series with higher frequency data, while accounting also for macroeconomic fluctuations. In addition, most of the research that has concentrated on long-run relationships have done so since the early part of 2000, thus avoiding the challenges involved in modelling periods of instability in series with high persistence and large fluctuations. Another aspect, which has also been overlooked and deserves a great deal of attention is that of the non-linear effects that oil shocks have on commodity prices and the implications of these in the behaviour of commodity prices. Finally, the literature, at this stage lacks a substantial number of studies that comprehensively embrace all the long-run aspects as well as volatility analysis of the crude oil and commodity price relationships along with macroeconomic variables. Moreover, considering the increasing financial investment on commodity markets, it is also important to determine the extent to which this new market tool affects commodity price and volatility.

1.1 Overview of Commodity Price Shocks

Commodities in general are categorised according to the physical characteristics and end use Figure 1-3. Commodity prices in general are historically notorious for their unpredictability and volatility. Nevertheless, within the past five decades, commodity prices have experienced a decline (in real terms) with the exceptions of two major price shocks[3]. These have taken place between the period of 1972-74 period and the most recent being that of 2006-08 and there is an evident decline in between these two periods (Figure 1-4). Also from Figure 1-4, it is evident that from the beginning of the series (with the exception of the positive price shock of 1973-194) up to approximately the early 2000s, there exists a clear period of very low (in relative terms) real price of non-energy prices. Somewhere after 2000 up to the present, the explosive upward trend in non-energy prices is evident. On the other hand, Figure 1-5, shows the real price index of energy commodities. This series, also experienced several periods of volatility as a consequence of both exogenous and endogenous shocks. Figure 1-5 shows a positive price shock between 1973-74 (in part as a consequence of the OPEC embargo) and later another price surge in the early 1980s, and more recently that of 2006-2008. Similar to the previous series, energy commodities also experienced a substantial decline after 1986 and a somewhat stable period since then until the early 2000s.

In terms of the source of these two non-energy commodity price shocks 1972-74 and that of 2006-08, there is very little agreement in the literature (even more so in the case of the 2006-08 shock). However, many authors point out similarities between these two events that might provide some insight into our understanding of the dynamics and channels through which commodity price shocks operate.

[3]Energy commodities might be an exception with a long history of endogenous as well as exogenous price shocks very well detailed by Hamilton [2011].

For example, as Gilbert [2010] points out, in both cases the agricultural price surge served as the background for a generalised commodity price increase. Also, as in the 2006-08 shock, the price increase of the 70s occurred in the presence of significantly large U.S. trade deficits and loose monetary policies. In these two periods, crude oil prices rose sharply. Additionally, as in 1974, also in 2008 the positive price shock was preceded by strong world economic growth and was followed by a deep economic rescission [Cooper and Lawrence, 1975]. Finally, "the magnitudes of the international price rises in 1973-74, and the speed of their subsequent fall, were very similar to those experienced in 2006-10" [Anderson and Nelgen, 2010]. Nevertheless, as stated by Gilbert [2010], there exists some substantial differences between the two events. For example, the 1974 commodity shock was short-lived compared to that of 2006-08 and the price increase for grains occurred after the crude oil price increases as contrary to the events of 1972-74.

Figure 1-3: *Classification of Commodities by Physical Characteristics and Sectors*

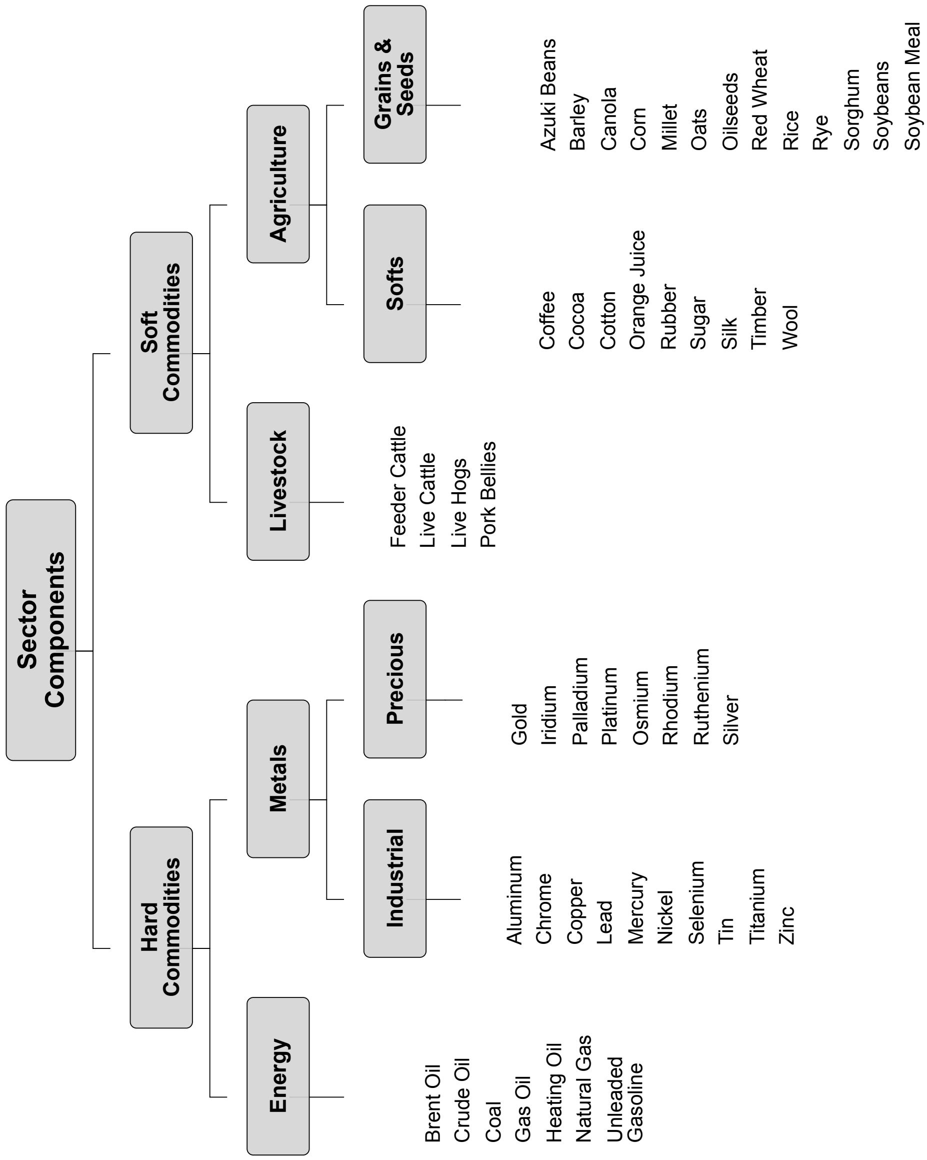
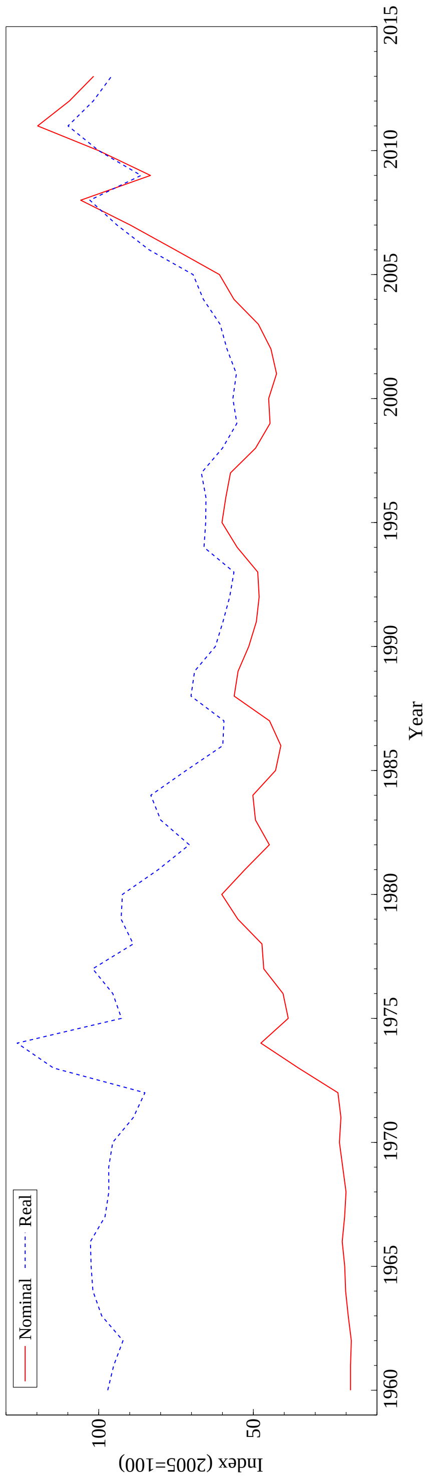
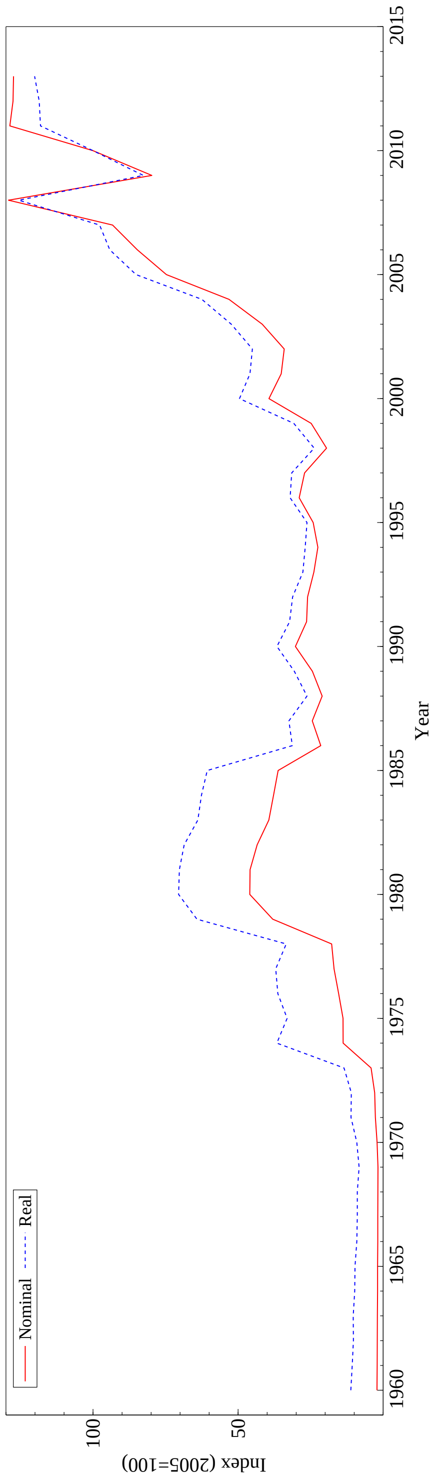


Figure 1-4: *Nominal and Real Non-Energy Commodities Price Index (2005=1)*



Data Source: World Bank Global Economic Monitor (GEM) Commodities.

Figure 1-5: *Nominal and Real Energy Commodities Price Index (2005=1)*



Data Source: World Bank Global Economic Monitor (GEM) Commodities.

1.1.1 The 1973-74 Commodity Shock

According to Cooper and Lawrence [1975] the 1973-74 commodity price shock was the most dramatic price increase in twenty years and some of these commodities saw their highest price on record. The timing of the commodity price shock of 1973-74 was not the same across all types of commodities, although the significant and sudden upward pressure in price was the same across virtually all of them. The peak of the agricultural commodity price shock occurred in the summer of 1973 and for some of them it also peaked in the summer 1974. However, the literature is not in full agreement with respect to the sources that triggered the shock, but some common factors have been clearly identified.

A number of determinants associated with the commodity price shock of 1973-74 were identified by several authors (For example, Cooper and Lawrence [1975] and Reinhart and Borensztein [1994]). These determinants comprise macroeconomic effects as well as demand and supply factors. More precisely, short-run supply shocks arise in the commodity markets as a consequence of adverse wheather and climate conditions, political and social unrests, labor strikes, pests and plant diseases [Carter et al., 2011]. In turn these demand and supply factors contributed to what experts consider the most important point in the commodity price crisis of the 1973-74: the low levels of stock to utilisation ratio which reached 15 percent by the beginning of the crisis in 1973.

Among the common macroeconomic factors associated with the commodity price boom, economists have identified the accelerated level of inflation in the early 1970s and large deficit the United States was running. The effects of monetary policy, and in particular that of the effects of exchange rates on agricultural commodities, was being studied in the post-World War II period. Economists had argued that, during this period, the dollar had been overvalued and that the effects of this disequilibrium contributed to the decline of prices in the agricultural market in the U.S. [Josling et al., 2010]. On the other hand, before the 1973-74 commodity shock, the Federal Reserve Bank was applying an expansionary monetary policy, with the aim of ameliorating the increases in the real price of energy [Carter et al., 2011]. This policy, also implemented by a number of other industrialised countries, flooded the world's international reserves with U.S. dollars, which at the same time caused a large depreciation of the U.S. dollar against major currencies. As a result of this policy, the real-commodity price boom of the early 70s, became a a sudden price bust in the early parts of the 1980s [Rausser et al., 1986].

On the other hand, Reinhart and Borensztein [1994] state that among the factors influencing the commodity price shock of the 1970s are "the state of the business cycle in industrial countries and the real exchange rate of the U.S. dollar." Similarly, Cooper and Lawrence [1975] suggested the devaluation of the U.S. dollar against the German mark by 36 percent between January 1973 and June 1975 was an important factor in fuelling commodity prices. Since commodities are traded in U.S. dollars, any depreciation on this currency would have made the trading price of these commodities cheaper relative to currencies in other industrialize economies such as those of Europe and Japan. Nevertheless, Cooper and Lawrence argue that "the importance of movements in exchange rates on prices of commodities lies not so much in changes in the unit of measurement as in the psychological effect of fluctuating exchange rates on speculative demand" [Cooper and Lawrence, 1975]. According to Carter et al., the commodity price decline of the 1980s was a consequence of the policies of the Federal Bank in an attempt to reverse the decline in the U.S. dollar in the early years of the decade.

One of the most convincing source of the surge in commodity prices of the mid 1970s is related to demand factors. According to Cooper and Lawrence [1975], the percentages changes in commodity prices during this period are better explained through the changes in the world's industrial production index. For example, the authors argue that in the year of the commodity price peak (1973), the industrial production index also peaked in the OECD countries (including the U.S. and Japan) and the World registered a 9.9 and 8.9 percent increase respectively. This increase was the largest since the 1950's in the case of the OECD countries and since 1960 for the world economy.

In addition to demand related issues, economists also believe that a number of supply factors were also involved in the 1970s upward pressure on commodity prices. Among these supply factors Cooper and Lawrence cite: (1) Poor harvests in the USSR and in southern Asia in 1972, which resulted in the world shortage of grain; (2) the reduction of 62 percent in the Peruvian anchovy catch between 1970 and 1972, which as a consequence increased the upward pressures on animal feeds (e.g. soybean meal)[4]; (3) after the increase in grain prices of 1972-73, a large quantity of land was shifted from producing cotton to grains, which resulted in a shortage of cotton in the market; (4) finally, political unrest in major exporters of metals (e.g. Chile, Zambia) disrupted the supply of various metal commodities to the market. Regardless, Cooper and Lawrence conclude that the supply-side factors, are only able to explain approximately 3 percent of the total variation in commodity prices during the price surge.

[4]As a consequence, Cooper and Lawrence and Carter et al. set as an example the fact that as a consequences of the increasing prices of animal feeds and demand for red meat, during the 1973 shock the livestock index increased by 80 percent increase between 1973 and 1974.

In summary, the 1973-74 commodity crises was a combination of demand and supply factors. Although experts agree that demand factors were the main determinants that triggered the surge in commodity prices. Therefore, the combination of demand (endogenous) factors in conjunction with supply (exogenous) shortages and some speculative markets played a role in the commodity price boom of the 1970s. Nevertheless, as the next section will demonstrate, very similar reasons can also be used to explain the determinants of the price shock of the 2006-08.

1.1.2 The 2006-08 Commodity Price Shock

A number of studies conclude that a strong demand for commodities (as it was in the 1973-74 commodity price shock) from the early 2000s was one of the main factors that contributed to the commodity price shock of 2006-08. The increasing demand pressures depleted the stock to utilisation ratios of several commodities, which was then related to upward volatility in commodity prices. In 2008, the stock to utilisation ratio for grains and oilseeds was as low as in the events that lead up to the 1973-74 commodity price shock [Piesse and Thirtle, 2009]. Consequently, it is crucial to understand what factors contributed to the stock-to-utilization ratio decline to such low levels.

In explaining the commodity price shock of 2006-08, Gilbert [2010] (as Cooper and Lawrence did for the 1970s price shock) argues that "common (macroeconomic and monetary) demand-side factors" are essential factors in helping to explain the dynamics in agricultural commodity prices during this period[5]. Similarly, Radetzki [2006] also agrees with Gilbert [2010] when he states that, as in prior commodity price surges, the 2006-08 shock, "was importantly triggered by

[5]For a more detailed explanation of the components of commodity demand and supply shocks, see for example, Carter et al. [2011].

a demand shock." Although there appears to be a consensus that there existed common factors affecting both (1973-74 and 2006-08) commodity price shocks, there were a number of unique factors in the latest shock, which in the view of many experts, have changed the nature of commodity prices in the economy.

The similarities between the 1970s commodity price shock and that of 2006-08 were many and by no means surprising to most economists. For example, a number of studies note that, as was the case in years before the commodity price shock in the 70s, before 2006, economic growth in the OECD region was very strong with historical highs of 3.3 percent for GDP and 4.1 percent for industrial output [Radetzki, 2006]. Primarily, from low-and middle-income countries such as China and India and their strong future growth prospects (See for example, Alexandratos [2008], Frankel and Rose [2010] and Abbott et al. [2011]). However, the Chinese economy has been the one that appears to bring the most pressure on commodity prices particularly for soybean and crude oil. According to the International Energy Association in 1986 China was a net exporter of crude oil (with an import dependency of -36 percent) and by 2008 it was a net importer of crude oil (despite being the fifth largest producer of crude oil) importing 51 percent of its demand [IEA, 2012]. Moreoever, Albanese [2006] (as cited in Radetzki [2006]) notes that China's demand growth for commodities has not been limited to energy commodities alone. For example, the same author singles out the "unsustainably extreme" demand of commodities by the Chinese economy. In particular, the author states that China's demand growth for aluminium, as share of total global demand, is more than 50 percent, 84 percent for steel and 95 percent for copper (Albanese [2006], as cited in Radetzki [2006]). Therefore, a number of studies point out the rapid economic growth and hunger for primary inputs of production as one of the main reasons for the upward pressure on commodity prices in the 2006-08 period.

A second parallel event in the 1973-74 and 2006-08 commodity price shocks is the relaxed monetary policy of the monetary authorities in the U.S. that was implemented between 2001 and 2004. Although the evidence is inconclusive in determining the extent to which monetary policy had played a role in the price surge of 2006-08, it is worth mentioning that prior to the price shock the Federal Reserve had actively targeted the reduction of the real interest rate. For example, Frankel and Rose [2010] believe that "easy monetary policy was at least one of the factors contributing to either the high demand for, or low supply of, commodities" in the period of 2006-08. The authors argue that one of the reasons for the commodity price crash of the 1980s was a result of the substantial increase in the real interest rates. The way in which this effect operates is that as real interest rates are increasing the opportunity cost of holding inventories also increases. Therefore, high real interest rates decreases the incentive for commodity producers to increase the supply of these commodities to the market. For example, at higher real interest rates, a net crude oil exporting country would benefit from higher returns to capital from supplying more crude oil to the market as supposed to keeping the oil in the ground. Thus, as the Federal Reserve decreased the real interest rate, it also lowered the incentives for producers to increase supply by lowering the cost of holding reserves, which decreased global supply and increased the demand for commodities [Frankel and Rose, 2010]. In a recent study, Hayo et al. [2012] used a GARCH model to analyze the effects of monetary policy on commodity price volatility. The authors, concluded that the U.S. monetary policy had a significant effect on the volatility of commodity prices, even more so since the changes to the expected target interest rate.

The decrease in the real interest rate in the U.S. leads to the third common factor between these commodity price shocks, which was the devaluation of the U.S. dollar against major trading currencies from 2002 until 2008. During this period, the U.S. dollar depreciated approximately 35 percent against the euro and about 40 percent with respect to major currencies [Carter et al., 2011, Mitchell, 2008]. The depreciation of the U.S. dollar, in turn, increases the dollar priced commodities with an estimated responsiveness to fluctuations in the variability of the U.S. dollar of about 50 to 100 percent [Baffes, 1997, Gilbert, 2008]. A complementary study to these is that of Kwon and Koo [2009] where the authors use a vector moving average (VMA) model for the period between 1983 to 2007 to estimate the relationship between agricultural commodities and macroeconomic performance. Kwon and Koo conclude that "unexpected movements of the exchange rate as well as interest rate are the main macroeconomic shocks causing fluctuations in the agricultural sector, although the agricultural income variation is due to the money supply shock consistently over time." More recent studies have found robust and conclusive evidence in support of these claims. For example, Chen et al. [2010] and Chen et al. [2011] found that when including exchange rates in their model, they find strong Granger-causal evidence between exchange rates and commodity price indices as well as their ability to predict these indices increasing. The evidence in the literature is extensive and overwhelming in supporting the effects of monetary and macroeconomic performance on the fluctuations of commodity prices in the most recent as well as the past commodity price shocks.

Finally, another common event was the similarity among the commodities that saw the strongest price movements. For example, crude oil prices experienced a sharp increases in the years between 1973-74 as much as they did in the

2006-08 period[6]. Additionally, in the 1973-74 commodity price shock, the price of cereal grains (e.g. corn, rice and wheat) increased more than three times as it was the case during the 2006-08. Evidently, there were a number of other factors that interacted with each other that were also common in both cases, for example authors have mentioned that there were a number of harvest failures, a number of different policy changes in order to reduce stock and to increase demand by several countries, a great deal of speculation in the financial sector as well as increases in the costs of production (e.g. energy, fertilisers, etc) (For more detail, please see: Trostle [2008]). In general, in both events, all commodities, particularly food and energy, experienced sudden increase prices co-movements [Carter et al., 2011].

Despite the number of similarities between these two price shocks, there were several aspects of the 2006-08 shock that indicated a profound change in the relationship between commodity prices and economic performance. For example, Carter et al. cites that the "agricultural commodities led the 1973-74 commodity boom but they moved concurrently with energy prices in 2007-08." While in the 2006-8 commodity price surge cereal grains, vegetable oils, energy and metals were responsible for most of the variation in price, only the first three were responsible for price changes in the 1970s [Carter et al., 2011]. More importantly, the 2006-08 commodity price shock saw in the increasing use of food commodities as energy, through the implementation of the biofuels policy of the mid-early 2000s, a powerful ally in the price increases. The latter factor has been the source of significant attention in the literature and deserves more attention and a closer analysis of its own.

[6] Although, it is worth noting that the reasons for this price shocks on crude oil were different between these two periods. In the case of the crude oil shock of 1973 was caused by the OPEC embargo Hamilton [2011].

1.1.3 Biofuels and the 2006-08 Commodity Price Shock

One of the main factors to blame for the commodity price shock of 2006-08 is the increasing use of subsidies and trade barriers by the U.S., Europe and Brazil to encourage the production of biofuels. Together, these three regions, contain about 89 percent of the world's biofuel production [Carter et al., 2011]. In the U.S. the policy responsible for increasing the production of biofuels (in particular that of ethanol) was the Energy Act of 2005 and Energy Independence and Security Act of 2007 [EPA, 2005, 2007][7]. This policy alone has drawn a considerable amount of land and resources out of the food market and transferred these to the biofuel industry. The fact is that almost all ethanol in the U.S. is produced by using corn. The U.S. is the main exporter of corn to the world and Carter et al. [2011] estimated that in 2010 the U.S. diverted 40 percent of the total corn output to the production of ethanol alone. Not surprisingly the FAO [2008] estimated that in 2007 approximately 75 percent of the growth in corn demand (about 40 million metric tons) could be traced to the production of ethanol. Moreover, Carter et al. states that during 2007-08 in the U.S., corn acreage increased by 19 percent while at the same time soybean land allocation fell by 16 percent. Many attribute this shift in land allocation to the price increases in soybean and blame the U.S. biofuel policies for their outcome. As a consequence, a number of studies have tried to estimate the effects of this policy on the magnitude of the corn price shock of 2006-08 with estimates ranging from anywhere between 20 to 35 percent [FAO, 2008, Roberts and Schlenker, 2009].

[7] For a more complete history of the evolution of biofuel policies in the U.S., please see Klass [2003] and Tyner [2008].

1.1.4 Link Between Biofuels and Agricultural Commodity Prices

The link between energy prices and agricultural commodities has always been present. Historically, high energy prices have influenced agricultural commodity prices through increasing costs of production (i.e. by increasing the costs of fertilizers, pesticides and transportation costs). Nowadays, the relationship between crude oil and agricultural commodities has been strengthened by adding biofuels to the equation. Today, high (low) crude oil prices act as a price floor (ceiling) for agricultural commodities [Schmidhuber, 2006]. Biofuels (e.g. ethanol and biodiesel) are predominantly produced by using agricultural commodities such as corn and soybean, which in turn are also used as inputs in other food related industries. The consequences of this complex relationship were evident in the 2006-08 commodity price shock where both crude oil and commodity prices increase to historically high levels.

The increasing demand for biofuels during 2000 and 2007 has had an estimated effect of a 30 percent increase in the weighted average of cereal prices Von Braun et al. [2008]. There is no doubt that the biofuel policies implemented in the early years of the century have added a new variable to the already complex and unstable relationship of commodity prices. Adding to this already complex relationship, we have that biofuels are both substitutes and complements to energy commodities derived from fossil-fuel; in addition, these energy components, are inputs to the production of food and agricultural commodities. Thus, biofuels affect commodity markets through the allocation of resources in the energy and agricultural commodity markets. For example, ethanol is used as an additive in the production of gasoline (regularly about 10 percent). Ethanol (as is the case in the U.S.) is primarily produced using corn, which at the same time is used as feedstock for livestock feeding. At the same time, corn also competes with other commodities for the same resources (e.g. water and land), causing these to rise as well. Therefore, in an effort to understand the relationship between biofuels and agricultural (food) commodities it is important to establish an economic framework to explain this relationship.

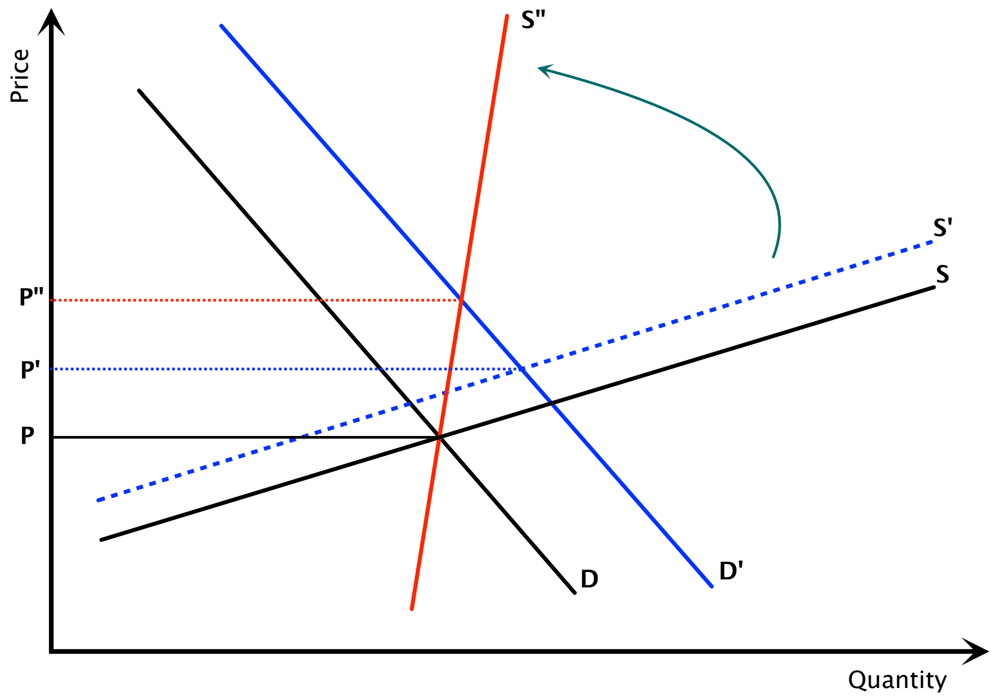
The fluctuations in commodity prices can be explained through demand and supply shocks and their corresponding channels. Gilbert [2010] presents a compelling argument showing that demand shocks are responsible for a greater magnitude of fluctuations in the price level of commodities than supply shocks. Gilbert explains his analysis as departing from the equilibrium point in Figure 1-6 where the initial demand curve (D) and supply (S) intercept, shown at price (P). If the system suffers a demand shock from D to D', this results in a price increase from $P \rightarrow P'$. As Gilbert argues, if the demand shock is common across a number of commodities the analysis is more complex. That is, an increase in the price of corn, in turn increases the competion for the same resources as other agricultural commodities (e.g. soybean), which in turn increases the costs of feedstock and results in higher prices for meat production. This complexity can be reflected in Figure 1-6 by the shift of the supply curve from S to S'. Moreover, as corn competes with other commodities in the market for similar factors of production, supply becomes more inelastic, which is represented by the turning over on is own axis resulting in S''.[8] As a consequence, the price resulting from the demand shock has now increased considerably from $P \rightarrow P''$.

The implications of the Gilbert [2010] model are of great interest for the analysis of the relationship between biofuels (and consequently crude oil) and com-

[8]Please see Gilbert [2010] where an analytical explanation of the model is provided.

modities markets as a whole. The first conclusion one arrives at is that demand shocks are more significant than supply shocks if analysed from an aggregate level. As a result, it is evident that demand shocks that affect several commodities have a greater affect than if it only affects a single commodity. Furthermore, the authors argue that shocks affecting commodities in a general manner, are likely to be derived from macroeconomic cycles. Moreover, due to the policies adopted for supporting biofuel production, in the presence of high energy prices (as seen in the 2006-08 rice shock), the dynamics of commodity prices, biofuels and energy commodities (particularly crude oil) become closer than ever before.

Figure 1-6: *Commodity price response to demand shock.*



Source: The figure was taken from Gilbert [2010].

1.1.5 Crude Oil Effects on Agricultural Commodities

One way in which crude oil prices affect agricultural commodities is through their positive effect on the costs of production. The pass-through of crude oil prices on non-energy commodities was studied by Baffes [2007]. Baffes used data from 1960 until 2005 (this included 35 internationally traded commodities and crude oil) and found that the overall pass-through of crude oil price changes to the overall non-energy commodity price index was 0.16. Additionally, Baffes conducted a disaggregated analysis and concluded that the highest pass-through index was that of fertilizers with a pass-through estimate of 33 percent, followed by agricultural commodities with a pass-through of 17 percent of any crude oil price changes[9]. Nevertheless, with biofuels in the picture, this adds a new dimension to the complexity of these commodity prices.

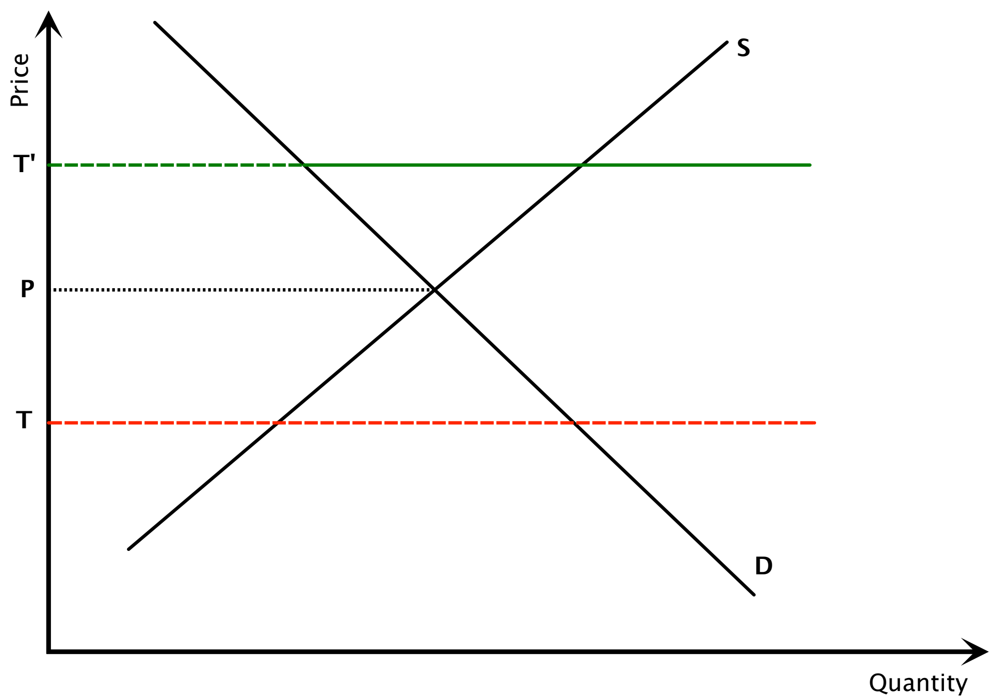
A number of authors have attempted to explain this link using a theoretical models. For example, farmers are indifferent to the end use of the agricultural commodity they produce. In that sense, farmers will sell their products to an ethanol or biodiesel plant, food or feeding processor according to the willingness to pay for the commodity in demand. Evidently, if the willingness to pay for a particular commodity by a biofuels producer is higher than that of a food or feeding industry, undoubtedly farmers will sell to the highest bidder. Biofuel prices are strictly related and driven by crude oil prices. Therefore, crude oil prices drive the price of biofuels, which then influences the price of agricultural commodities.

Increasing crude oil prices acts as a catalyst for biofuel demand, which then

[9] Other studies have focused on the effects that biofuels have on energy commodities such as natural gas, see Whistance et al. [2010].

drives agricultural prices upwards. This relationship has been closely described by Schmidhuber [2006], who concluded that given the price of derivatives from crude oil is equal to or exceeds the costs of producing biofuels, the market for fossil fuels causes an excess of demand for agricultural commodities. In essence, this is how Schmidhuber concluded that the link between crude oil prices through biofuels and agricultural prices sets a price floor or ceiling for agricultural commodities. This claim can be explained by using the diagram from Figure 1-7.

Figure 1-7: *Commodity price response to biofuels demand.*



Source: The figure was taken from Gilbert [2010].

Schmidhuber argues that crude oil prices and fertilizers determine the break-even price for the agricultural commodity from which biofuels are produced at no profit. In Schmidhuber's model there exists two distinct possibilities: (1) when crude oil prices are high; (2) and crude oil prices are low. If crude oil prices are low, Schmidhuber states that the clearing price (P Figure 1-7) for the agricultural commodity will be higher than the break-even price for biofuels (T) and therefore economically unfeasible. In this scenario, the price of agricultural commodities would be determined independently from the price of oil and biofuels. In the second case, if crude oil prices are high, then the incentives to carry on biofuel production are set since the price of agricultural commodities is lower (P) than the price threshold to produce biofuels (T'). As long as the price threshold price remains above that of agricultural commodities, the price of the latter will be determined by movements in the price of crude oil. Therefore, subsidies and tariff policies imposed to lower the costs of biofuel productions raise the threshold price even in cases when the price of crude oil might not be as high as the level needed to reach T'.

This study is thus one which will attempt to bring all of these characteristics together in order to further improve our understanding of the mechanisms as well as channels through which crude oil and commodity prices are affected. There are three areas of interest I will address in the following empirical studies: (1) The long-run relationship between agricultural commodities with crude oil and macroeconomic variables; (2) The relation between price volatility in agricultural markets and that of oil and several macroeconomic variables; (3) Finally, I will provide some enlightenment on the factors affecting agricultural commodity price returns and explore in depth the arguments on the financialization of commodities and its impact on price volatility.

The contribution to the current body of literature are significant and enhances our understanding of both long and short-run dynamics of food and agricultural commodity price dynamics in the past thirty years. In particular, the first section of this research increases the current body of the literature by modelling the long-run relationship of two major commodity prices including macroeconomic factors and energy prices simultaneously. Also, this study contributes to the literature by modelling cross-correlation between the same set of commodities returns with oil prices and macroeconomic factors. This is essential to understand the impact of energy policies spillover into agricultural markets particularly after the biofuel revolution in the early parts of the century. Also, it offers insights into understanding the extent to which these commodity prices are affected by macroeconomic cycles specially if it is linked to exchange and interest rates. This would allow us to gain valuable insights into the role of monetary policy and its relation to energy and agricultural commodity price changes. Finally, I investigate the extent to which commodity futures indexes and the financialization of commodities have impacted spot return prices in commodity and energy markets.

CHAPTER 2

A COINTEGRATION ANALYSIS OF FOOD, CRUDE OIL PRICES AND MACROECONOMIC VARIABLES

2.1 Introduction and Overview

In the recent years there has been an extensive argument on the comovement between crude oil prices and agricultural commodities. This was lead by the commodity price surge starting in 2006 through 2008 as well as the energy policies implemented in during the same period that linked food commodities with energy demand. Consequently, many researchers have carried out studies in an effort to understand the transmission mechanisms through which this linkage operates. The literature mainly suggests two channels through which this relationship takes place. The first is through a cost-push effect by the increasing biofuel demand as a result of the bioenergy policies implemented in the early years of the last decade. Another link is that which operates through macroeconomic fluctuations such as interest rates and exchange rates. However, few studies have attempted to capture the extent to which these channels operate in the long or short run price dynamics of agricultural commodities. In this study

I concentrate on the analysis of the effects of crude oil shocks, exchange rate and fiscal and monetary policy explain the long run price fluctuations of three commodity prices.

The aim of this chapter is to determine the extent to which three major world food commodities have been affected by crude oil prices and the macroeconomy. Additionally, we are interested in examining if aggregate demand shocks and oil-specific shocks have a permanent effect on these commodities. Over the years there has been an increased interest in international commodity markets, following the rise in price levels leading to up the 2008 financial crisis and the subsequent bust. The commodity markets are an increasingly important part of the world economy, especially since commodity price fluctuations are expected to become more pronounced [Carter et al., 2011] and are often associated with macroeconomic volatility [Céspedes and Velasco, 2012]. Therefore, in order to achieve a level of fiscal stability, whether you are a net exporter or importer of primary commodities, it is essential to understand the global factors and dynamics affecting commodity markets.

In the wake of the energy and commodity price surge of 2006-08, economists became concerned with understanding the causes of world commodity price fluctuations. In particular, they paid close attention to two distinct areas of research. The first was concerned with the impact of rising biofuel production on food commodity prices (e.g. maize, soybeans and sugar). This area of research arose in order to explain soaring global food prices during this period after the adoption of biofuel production policies. As a result, this body of literature has concentrated on studying the impact of local subsidies fostering biofuel industries to offset increasing global energy prices in major grain and food markets such as

Brazil, the U.S. and Europe[1]. The second body of empirical studies has aimed at understanding the causal relationship between global food commodity markets and world crude oil prices. The latter, is the main focus of this paper. We are mainly interested in understanding the dynamics affecting global food price cycles through macroeconomic and crude oil price fluctuations.

The recent global price surge in energy and commodity markets have motivated the interest of economists to establish the underlined forces driving this relationship. Consequently, research has recently concentrated on determining the driving factors and channels through which energy and commodity price cycles are affected. In efforts to explain these dynamics, a significant number of studies such as these by Carter et al. [2011], Céspedes and Velasco [2012], Jacks [2013], Kilian [2008a], Spatafora and Tytell [2009], Wright [2011] have provided theoretical and empirical evidence for some of the reasons behind the most recent energy and commodity price fluctuations. Broadly, these can be categorized into demand and supply-side factors.

There are four demand-side factors that have been considerably studied in order to explain past and recent agricultural commodity and energy price increases. One of the most prevalent demand-side factors discussed in the literature is the increasing wealth by the BRIC (Brazil, Russia, India and China) and other developing nations within the past decade. This wealth effect is thought to have triggered greater global demand for energy and agricultural (food) products and together with a relatively flat production was responsible for the 2007/08 price surge [Cairns and Meilke, 2012, Josling et al., 2010]. Thus, as a number of authors claim, the last energy and commodity price shock is a result of primarily the

[1] Zilberman et al. [2013] provides a succinct review of this body of literature.

unprecedented demand from developing markets as a result of this wealth effect [Abbott et al., 2011, Hamilton, 2009][2]. By analyzing the dynamics of a number of demand-side factors before the 2007/08 commodity price crisis, Hamilton [2009] offers important contributions to understanding the causes leading to this episode. The author concludes that an important contributor to high crude oil prices (during this period) was the greater energy demand as a consequence of increasing wealth from developing nations (particularly that of China)[3]. Similarly, Kilian and Hicks [2013] provides empirical evidence supporting the view that strong (and unexpected) growth in emerging economies is able to explain the increase in the real world price of crude oil during the commodity and energy price shock of the mid 2000s. Consequently, the literature suggests that increasing income, and in particular from developing nations, is a crucial element in determining the price dynamics leading to the recent oil price crisis.

Greater demand from developing nations, as a consequence of their income effect, is argued to be responsible not only for the price increases in the global energy sector, but also in the agricultural commodity markets. For instance, Cooke and Robles [2009] suggests that the purchasing power gains from developing nations, as an important element in increasing local demand for meat which in turn increases the demand for livestock, which competes with feedstock commodities such as maize and soybeans (See also, Henderson [2011], Zhang and Law [2010] for more details on equivalent arguments). Contrary to these arguments, Headey and Fan [2008] argue that demand from emerging economies particularly from China and India cannot alone explain the increase in agricultural food commodity prices during this period. More precisely, Headey and Fan state that China

[2] In addition, there are also external factors such as stagnant world production of crude oil in previous years and historical low stock-to-use ratios.

[3] According to Leung [2010], between 2003 and 2007, China's oil demand alone, was responsible for approximately 37.1% of the increase in world oil consumption.

during the years leading up to the commodity price crisis (2000-2007) imported approximately 20% less wheat than the preceding period while India's imports of wheat and corn remained insignificant relative to the world's imports. However, Headey and Fan [2008] conclude that at least in the crude oil and oilseeds market, increasing demand from emerging economies might explain some of the variation in global prices during this period. Consequently, if there is a causal relationship between crude oil and food commodity prices, there exists a possibility of some of the feedback in the oil market being transmitted to the agricultural food commodities. Therefore, global real economic activity appears as an important determinant of world agricultural commodity prices and should be considered in the analysis of price dynamics.

Another important demand-driven component affecting price dynamics in agricultural markets, is the increasing production of biofuels using agricultural commodities. The rise of biofuels production fostered by government subsidies and tax incentives, has expanded the supply of these products towards biofuel production and away from food production. The biofuel revolution has significantly taken from the food chain large quantities of grains and vegetable oils as their primary inputs, which are competing with food crops for resources, such as land and water [Chen and Khanna, 2013][4]. For instance, Mitchell [2008] cites the increasing production of biofuels in both the U.S. and EU markets as the crucial trigger for the 2007/08 food price crisis. Also, Tyner [2010] points out the strong correlation during 2008/09 between crude oil and ethanol with corn prices (0.95 and 0.84 respectively) as evidence of the significant shift in the fuel to food price dynamics. More recently a study conducted by Condon et al. [2013] estimates that in the U.S. "each additional billion gallons of ethanol causes a

[4]See also Colin Carter and Smith [2012] and Roberts and Schlenker [2013] for additional discussions in this subject.

5-10 percent increase in corn [nominal] prices." Nevertheless, while a number of authors have argued that the introduction of ethanol feedstocks has had a significant impact on food commodity prices, recent studies have highlighted that this impact is much less significant than economic growth [Zilberman et al., 2013].

A third determinant of the energy and commodity price dynamics is derived from the U.S. macroeconomic policies influenced by its monetary policy, exchange rate and inflation. Abbott et al. [2011] and Headey and Fan [2008] have singled out the weak U.S. exchange rate in the years leading to the peak of the 2008 commodity price as one of the main drivers of energy and agricultural commodity prices. Since all energy and agricultural commodities are traded in U.S. dollars, as this currency depreciates (e.g. expansionary monetary policy) with respect to major trading partners, then commodity prices rise since now the international purchasing power has increased (the opposite effect occurs if the dollar appreciates) [Phillip and Friederich, 2013]. On the other hand, Bernanke et al. [1997] and Barsky and Kilian [2001] have argued that loose monetary policy is responsible for the energy and commodity price shocks of the late 1970s and that anti-inflationary policies in the subsequent decade drove prices down. The argument is very intuitive as there exists a negative trade-off between holding cash and storable commodities as interest rates increase. For example, low interest rates (i.e. expansionary monetary policy) today, results in higher prices by increasing demand for commodities as a consequence of the lower costs of borrowing, which acts as a positive incentive to purchase and stockpile storable commodities with the intention of having positive returns in the near future [Frankel and Rose, 2010]. On the other hand, real exchange rates have been shown to share a long-run equilibrium with a number of commodity prices in addition to being the long-run adjustment force for a number of these commodity prices [Cashin et al., 2004]. Therefore, it is evident that from both on empirical and theoretical perspective, macroeconomic variables affect both the energy and agricultural commodity markets and should be included in the analysis.

The last, but not the least, factor affecting these markets is the increasing flow of capital or financialization of future contracts in the energy and agricultural commodity markets, which is also thought to have contributed to the price increases in the last decade. The financialization of commodities has been argued to allow room for speculative trading behavior and consequently to be responsible for the large swings in volatility during the last commodity price boom. Tang and Xiong [2012a] showed that "index-related instruments" increased from $15 billion in 2003 to approximately $200 billion by the middle of 2008. In the same study, the authors conclude that as a result of the financialization process of commodities, demand and supply are not the sole determinants of individual commodity prices, but to a large extent their price is determined by the entire financial sector. These findings are also corroborated by recent empirical work by Pen and Sevi [2013]. Here, the authors summarize their findings by stating that non-market fundamentals (i.e. supply and demand) explain approximately 60% of the price variations. However, Kilian and Murphy [2014] find no evidence that speculation is responsible for the 2008 crude oil price peak; instead, substantial evidence is provided showing that market fundamentals were responsible for the price surge. More recently, Hamilton and Wu [2015] corroborates this previous study by finding no evidence that speculative positions of investors were able to drive future agricultural commodity prices. Similarly, Hamilton and Wu [2014] show that before 2005, investors who consistently took long positions on crude oil futures contracts received on average positive returns on their investments; however, after this period, the authors find substantial evidence supporting the contrary result from the previous sample period. In summary, although early evidence in the literature supports the non-market fundamentals theory as an explanation for increasing price shocks in the commodity market, recent work indicates even though there are instances where speculation is present, in the long-run the main drivers of commodity prices are economics fundamentals and more precisely demand-side factors.

Finally, there are also supply-side factors that have contributed to the commodity price surge in the past years. Although some of the supply shocks are associated with having long-run effects on price variability (e.g. low growth in agricultural production as a result of a lack of investment in R&D), a significant source of price shocks in the energy and agricultural commodity markets are associated with short-run disruptions. For the most part, supply shocks arise from social and political unrest, drastic changes in weather patterns as well as the higher inputs costs of fertilizers and transportation[5]. This last, is an important aspect to consider, since price increases in crude oil affects agricultural commodities not only as an input, but also as oil prices increase so do the price of ethanol and other biofuels and therefore more grains and vegetable oils are redirected from food to energy consumption [Mutuc et al., 2010]. Nevertheless, the literature provides significant empirical evidence showing that supply-side shocks are associated with having very low and temporary effects, relative to demand-side shocks, on both energy and commodity long-run price dynamics [Headey and Fan, 2008, Kilian, 2008b, 2009, Kilian and Murphy, 2012]. Consequently, since in the long-run supply-side factors are negligible in terms of being responsible for energy and agricultural commodity price increases in the past years, this characteristic is the main reason this study is focused on the demand-side factors.

[5]In addition to these, there are also factors affecting the world food commodity markets associated with population growth and dietary changes [Chakravorty et al., 2012].

We can summarize the recent shocks to oil and agricultural commodity price by a series of demand-side factors: (1) Increasing wealth in developing economies; (2) biofuel production; (3) financialization of commodities, which allegedly resulted in market speculation; (4) macroeconomic cycles. Even though oil and agricultural commodity prices share mechanisms through which prices can be disturbed, their long-run causal effects are still not agreed on in the literature. Therefore, this study will focus on determining the causal relationship between crude oil and a set of individual agricultural commodities considering a number of macroeconomic variables. In essence, this study hopes to contribute to the literature in offering an understanding of the extent to which world real crude oil prices have a long-term effect on agricultural commodities as well as considering macroeconomic channels through which these might also be affected. Thus, offering an understanding of the long-term channels through which maize, soybeans and sugar global prices are affected.

Following the introduction, I summarize the relevant literature on the long-run analysis of energy and commodity prices and subsequently there is a discussion of the methodology used in this study. Section 2.4 describes the data and Section 2.5 discusses the results. Finally in Sections 2.6 we conclude and discuss some policy implications of the results.

2.2 Literature Review

The literature on the causal effects between crude oil and commodity prices is vast. The price co-movements in commodity markets is thought to take place because macroeconomic and market fluctuations are common to all commodity prices. In the seminal paper by Pindyck and Rotemberg [1990], they showed that there existed unexplained price co-movements in seven raw commodities, which cannot be accounted for by market and macroeconomic fundamentals. In this case, the authors attributed these residual effects to herd behavior in the financial markets; thus, laying the foundations for the 'excess co-movement' hypothesis. Nevertheless, the literature has questioned the initial findings from Pindyck and Rotemberg, firstly by Leybourne et al. [1994] and subsequently by Deb et al. [1996] among others. The former, points out the non-stationay nature of commodity price series and thus the methodological deficiencies in the Pindyck and Rotemberg analysis. Therefore, Leybourne et al. [1994] apply a pair-wise co-integration analysis to evaluate Pindyck and Rotemberg's hypothesis and conclude that only in two out of fifteen pairs does such a phenomenon occur. Similarly, Ai et al. [2006] controlled for supply factors in addition to economic fundamentals and concluded that there is no excess co-movement within the agricultural commodity markets.

Within the past decade there has been a substantial number of studies concentrated on the impact of shocks in the crude oil market on food commodity prices. Yet, very few studies have emphasized the importance of understanding the fundamental economic forces underlined in this relationship. The great majority of these studies have focused their attention on the co-movements across individual commodities linked with crude oil prices. These studies have used time series analysis and in particular Cointegration and Vector Error Correction Models (VECM) in order to estimate both short and long-run dynamics among these markets. Nevertheless, and despite the large body of research on this topic, the literature is far from an agreement and results vary widely from finding no evidence of long-run relationship at all, to strong and positive long-run relationship.

One of the first empirical works to address the long-run relationship between crude oil and commodity prices is by Chaudhuri [2001]. The authors use a bivariate Johansen cointegration approach to model the effects of real oil price shocks on several primary commodities, using monthly data from 1973 to 1996. They conclude that all commodities analyzed (including maize and sugar), have a long-run relationship with real oil prices. Interestingly, the authors cite macroeconomic effects (e.g. low level of interests rate and increasing economic activity from developing economies) as explanatory variables in the rise of commodity prices during this period, but do not include any of these variables in their analysis. One of the first studies specifically concerned with the relationship between crude oil and food commodity markets, is that by Campiche et al. [2007]. Here, the authors main objective is to establishing a direct link between world crude oil and soaring food prices. In this respect, Campiche et al. concentrate their efforts in the co-movement between major food commodities (corn, sorghum, sugar, soybeans, soybean oil and palm oil) and nominal crude oil prices by using a bivariate Cointegration Vector Autoregressive (CVAR) model and VECM with weekly data from 2003 to 2007. The authors' conclusions vary in success and are unable to determine any long-run relationship (i.e. co-movement) among any individual commodity and crude oil for the 2003-05 period. Yet, they find a cointegrating relationship between corn and soybean prices with crude oil during 2005-2007 period; thus providing some evidence of strengthening relationship between energy and commodity markets during this period. On the other hand, Baffes [2007] examines the passthrough effect from real crude oil price shocks on several commodity indices using yearly data from 1960 to 2005. The authors also use a bivariate cointegration approach in order to estimate the long-run price elasticity of real crude oil prices and they determine that the passthrough effect is 16% for all commodities and 18% for the food commodity during the entire sample. More importantly, the authors recognize the simplicity of their model and thus the inability to capture the complex relationship of commodity price dynamics. Similarly, in a recent study by Ciaian and Kancs [2011b] using a bivariate CVAR/VECM with weekly data from 1994 to 2008, the authors analyze the long-run relationship between nine agricultural commodities and crude oil prices. In order to account for structural breaks in the series, Ciaian and Kancs split the sample into three distinct periods of four years each from 1994-1998, 1999-2003 and 2004-2008[6]. The authors conclude by providing evidence in support of the increasing interdependencies between agricultural commodities and crude oil prices in particular for the period between 2004-08. Although these studies have shed light on some of the circumstances in which oil and commodity prices were linked during this period, none of these studies accounted for the fundamental factors affecting both oil and commodity prices as possible explanations.

On the other hand, other studies have provided contradictory evidence (even when using similar methodologies, data span and frequency) showing that the literature is far from agreeing on the empirical evidence of the causal links between crude oil and agricultural commodities. For example, in a study by Yu et al. [2006], the authors apply a CVAR/VECM analysis using weekly data from crude oil and four edible oils prices from January 1999 to March 2006 in order to estimate the long-run relationship between these commodities. Contrary to previous finding, Yu et al. conclude that crude oil prices do not have a significant impact on the long-run behaviour of vegetable oil prices. In a another study, Zhang et al. [2009], also using a VECM, study the relationship between fuel (crude

[6]The authors do not offer a clear methodology used to determined the break points nor the events that might have induced these. The authors state that: "The segmentation of the sample corresponds roughly to structural beaks."

oil, gasoline and ethanol), corn and soybeans prices in the U.S. using weekly data from 1989 to 2007 and conclude that there exists no long-run relationship among these variables. Similarly, Zhang et al. [2010], using a longer data set and with a monthly frequency for a similar set of commodities, concludes that there is no long-run price relationship between crude oil and agricultural commodity prices and very weak evidence of short-run dynamics. Moreover, Saghaian [2010], also using cointegration analysis, rejects the hypothesis of cointegration between crude oil, corn, soybeans and wheat prices and is only able to show that crude oil prices Granger cause corn, soybeans and wheat prices. In summary, one of the main drawbacks of the current state of the literature, is the insufficient understanding of the transmission mechanisms into the relationship between crude oil and agricultural commodities. Consequently, there exists the need to move away from bivariate models and to incorporate fundamental economic factors in the analysis in order to capture the possible dynamics, if any, in this relationship.

A significant number of the studies have limited their attempt to model the long-run relationship between these variables using bivariate models and using relatively short periods of times that can not possible measure long-run variability. Moreover, there is not a theoretical reason to believe that there is a direct causal relationship between crude oil and commodity prices (other than as an input or transportation process). However, it is possible that the same underlying forces driving global crude oil prices (e.g. world demand factors) are also affecting commodity price cycles. Therefore, efforts to model long-run relationships between these variables using bivariate models may offer a misleading and incomplete understanding of the relationship dynamics. This might explain why some studies are able to find different conclusions even when using similar time periods, since the underlying forces driving this relationship might be strengthened and weakened independently of the variation between these individual variables.

In determining the transmission channels, a number of studies have singled out macroeconomic variation as a significant factor in driving oil prices as well as agricultural commodity prices. The link between the U.S. dollar exchange rate and commodity price cycles is also well discussed in the literature. Nevertheless, the underlying forces driving the dynamics of this relationship are yet to be understood. Commodity prices are quoted in U.S. dollars, thus it suggests that exchange rate fluctuations in this currency would be associated with commodity price fluctuations [Frankel, 2008]. Yet again, there is no reason to believe this is a direct causal relationship between U.S. dollar currency fluctuations and world commodity prices in the long-run. In fact, it is possible that the factors affecting the exchange rate (e.g. interest rates and the current account deficit) also affect the state of commodity price cycles. For instance, Gilbert [2010] argues that the co-movement experienced between exchange rate and commodity markets in general have the business cycles as a common component. Moreover, Abbott et al. [2011] point out that economic growth and the forces driving U.S. dollar exchange rate fluctuations are also important forces currently driving food prices. Similarly, Hamilton [2009, 2011] states that loose monetary policy is one of the drivers of the 2007/08 oil price shock. Therefore, in order to estimate any relationship between crude oil and commodity price it is crucial to also include macroeconomic variables since any causal effect from crude oil to commodity markets is likely to be overestimated or underestimated (depending on the relationship) in a simple bivariate CVAR model. Nevertheless, there is no study in the current literature that has incorporated the impact of all these macroeconomic dynamics to understand its effect in the global agricultural and food markets.

The effects of the U.S. dollar exchange rate have been addressed by a number of studies in the recent past, but only a few have been able to draw meaningful conclusions in the global market. Nazlioglu and Soytas [2012] examine both the short and long-run relationship between crude oil, lira-to-U.S. dollar exchange rate and a number of individual agricultural commodity prices in Turkey. They apply a panel cointegration analysis as well as Toda-Yamamoto causality tests to monthly data from January 1994 to March 2010. Nazlioglu and Soytas conclude that there is no long-run transmission mechanism between fluctuations in the lira-to-U.S. dollar exchange rate market and world oil prices to agricultural commodity prices in Turkey. On the other hand, Baek and Koo [2010] using an ARDL cointegration approach show that for the U.S. market, the exchange rate helps to explain variation in the short and long-run food markets. Other studies have concentrated their efforts on the effects of the U.S. dollar exchange rate on the world agricultural and food prices such as Gohin and Chantret [2010], Harri et al. [2009], Kwon and Koo [2009]. In the study by Harri et al., the authors are interested in estimating the relationship between world crude oil future prices and U.S. exchange rate with individual corn, soybean, soybean oil, wheat and cotton world future prices using cointegration analysis with data spanning from January 2000 to September 2008. The authors, split the data sample into two periods in order to find a cointegration relationship between the dollar exchange rate and oil future prices with corn from early 2006 to 2008. Kwon and Koo use a vector moving average (VMA) analysis and conclude that "unexpected movements of the exchange rate as well as interest rate are the main macroeconomic shocks causing fluctuations in the agricultural sector." On the other hand, Gohin and Chantret employ a Computable General Equilibrium (CGE) to model the macroeconomic linkages between a series of world food and energy prices. Gohin and Chantret's simulations conclude that macroeconomic variables provide a substantial explanatory power to the global energy and food price fluctuations.

Currently, the extent to which global markets for agricultural commodities have been affected by fundamentals factors as well as energy price shocks remains a subject of great debate and often produces conflicting results. Nevertheless, the most frequent methodologies for modelling this long-run relationship have been by using a Cointegration Vector Autoregressive (CVAR) approach. The advantage of using this methodology is that it allows researchers to determine both short and long-run parameters through a Vector Error Correction Model (VECM) as well as determining the pulling and pushing forces of the system of interest [Juselius, 2006]. However, the majority of these studies have relied on oversimplified relationships in order to measure the long-run dynamics of agricultural prices. In the first chapter, I will use a CVAR approach by incorporating a series of macroeconomic variables in addition to crude oil prices in an attempt to capture both short as well as long-run driving forcers of three agricultural commodity prices (maize, soybean and sugar). Also, as in Gilbert [2010], I will argue that fundamentals in the market for agricultural food commodities are the principal dynamics drivers of global prices. This study differs from those in the current literature not only by using observations over thirty years at a monthly frequency, but more importantly by exploiting the information dynamics through macroeconomic and energy prices together with agricultural commodities into one estimating system.

2.3 Methodology

The modeling approach used in the analysis is a cointegrated vector autoregresive (CVAR) proposed by Johansen and Juselius [1990] where first the cointegration space (i.e. long-run relationship) is estimated and subsequently we proceed by testing specific economic hypothesis within this space [Johansen, 1992]. Lets consider a general $p - \textit{dimensional}$ VAR model with order k lags in its vector error correction (VECM) form:

$$\begin{aligned} \Delta X_t = \Pi X_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-1} + \mu_0 + \mu_1 t + \Phi_1 D_t + \varepsilon_t, \\ \forall \ t = 1, 2, \ldots, T \end{aligned} \tag{2.1}$$

where the difference between the mean and the actual realization is a white-noise process with mean zero and covariance Ω (i.e. $\varepsilon_t \sim NI_p(0, \Omega)$). Thus, Equation (2.1) is consistent with agents who are rational in the sense that they do not make systematic errors based on previous realizations [Juselius, 2006]. The dimensions of parameters Π and Γ_i for $i = 1, 2, \ldots, k-1$ are $(p \times p)$ and $(p \times 1)$ for the parameters μ_0 and μ_1. The parameter Φ has dimension $(p^D \times p)$ and dimension $(p \times p^D)$, where D_t can include seasonal centered and intervention dummy variables in the form of transitory shock as well as mean-shift dummies[7].

Equation (2.1) provides a convenient formulation to analyze the dynamics of the system. In this case, the the short-run effects are given by Γ_i and the long-run effects (levels) of the model are captured by the parameters in Π. Provided that Π has a reduce rank $(r < p)$, that is, assuming Equation (2.1) contains a mixture of stationary and non stationary components, then there exists $p \times r$ matrices

[7] Transitory shock dummy variables (D_{p_t}) is a vector of $(\ldots, 0, 0, 1, -1, 0, 0, \ldots)$; the vector of permanent blip dummies is defined as $(\ldots, 0, 0, 1, 0, 0, \ldots)$; and the vector of mean-shift dummies (D_{s_t}) as $(\ldots, 0, 0, 0, 1, 1, 1, \ldots)$.

α and β, each of them with rank r such that $\Pi = \alpha\beta'$ and $\beta' X_t$ is stationary. In this case the number of cointegration relationships is determined by the rank 'r', while the adjustment parameters are found in the α matrix and $\beta' X_t$ represents the r number of cointegration relations. The cointegration relationships determine the deviations front he long-run dynamics between the variables and the coefficients in α measure the rate of adjustments to any deviations from the long-run relationship.

Cointegration is a powerful tool in order to understand both the short and long-run dynamics of agricultural commodities, crude oil and macroeconomic variables. This is because as long as there exists a cointegration relationship among these variables, it means that there is a stationary long-run equilibrium relationship between the individual non-stationary variables and in the cases where these diverge (pushing-forces) from this long-run equilibrium at least one of the variables in the system returns (pulling-forces) to the long-run equilibrium level [Juselius, 2006]. The fact that deviations from the long-run equilibrium are stationary, ensures that deviations from the long-run equilibrium (i.e. cointegration relationship) of individual variables are bounded despite these presenting path-dependent behavior. Therefore, by estimating a CVAR model we will be able to determine the pushing and pulling forces of this system of variables, thus helping us to predict both short and long-run behavior of food prices considering crude oil and macroeconomic dynamics.

2.4 Data Description

The objective of this analysis is to determine the long-run relationship as well as short-run dynamics between a number of macroeconomic variables as well as energy prices and the world price of three major agricultural commodities: maize, soybean and sugar. In particular, the study aims to determine the effects of four macroeconomic variables: inflation rate, real exchange rate, short-term interest rate, and the Kilian index for global economic activity as in Kilian [2009] in addition to world crude oil prices on these three agricultural commodities.

All data series have a monthly frequency and observations span from January 1982 until December 2012 (See Table: 3.1). In addition, all variables have been transformed using natural logarithms in an effort to obtain stable series in percentage terms and approximately linear [In and Inder, 1997]. The agricultural commodities of interest are the price of maize (MZ_t), soybean (SB_t) and sugar (S_t), which were all obtained from the IMF-IFS database and are measured in U.S. dollars per metric tonne. All these agricultural price variables are world benchmark price series which are representative of the global market and are determined by the largest exporter of this specific commodity[8].

Table 2.1: *Data Definition and Sources*

Variable	Frequency	Range	Units	Source	Code
Maize (MZ_t)	Monthly	Jan 1982 Dec 2012	U.S. Dollars per Metric Ton	IMF	PZPIMAIZ
Soybean ($SOYB_t$)	Monthly	Jan 1982 Dec 2012	U.S. Dollars per Metric Ton	IMF	PZPISOYB
Sugar (S_t)	Monthly	Jan 1982 Dec 2012	U.S. Dollars per Metric Ton	IMF	PZPISUG
Crude Oil (O_t)	Monthly	Jan 1982- Dec 2012	U.S. Dollars per Barrel	IMF	PZPIOIL
PPI (P_t)	Monthly	Jan 1982- Dec 2012	Index (1982=100)	FRED	PPIACO
Three-Month T-Bill (I_t)	Monthly	Jan 1982- Dec 2012	Percentage	FRED	TB3MS
Trade Weighted USD Index (XR_t)	Monthly	Jan 1982- Dec 2012	Real Index (1997=100)	FRED	TWEXBMTH
Indx. Global Econ. Activity (Y_t)	Monthly	Jan 1982-	Index	Lutz Kilian	-

[8] For more details on the definition of reference world prices and its benchmarks, please visit http://www.imf.org/external/np/res/commod/faq#q6

As a measure for the inflation rate, we have used the U.S. Producer Price Index (PPI) for all commodities (not seasonally adjusted) since the variables of interest are widely used as intermediate goods in for industrial production. The real exchange rate (XR_t) was obtained and constructed by the Board of Governors of the Federal Reserve System, and is defined as the weighted average of the foreign exchange values of the U.S. dollar against the currencies of major U.S. trading partners converted to real terms. For the short-term interest rate (I_t) we have used the three-month Treasury bill secondary market rate as reported by the Federal Bank of St. Louis in the FRED database (See Table: 3.1). Moreover, as a measurement of real global economic activity (Y_t) we use Lutz Kilian's index of global real economic activity in industrial commodity market as defined in Kilian [2009]. This index considers ocean freight rates as an observable real activity variable since in the short run the fleet of transport vessels is essentially fixed. The index is constructed by Lutz Kilian and it primarily represents the average freight rates for cargoes of grain, oilseeds, coal, iron ore, fertilizer, and scrap metal as reported by Drewry's Shipping Monthly[9]. Additionally, we also include the world price of crude oil (O_t) measured as the trade weighted average price of crude oil in U.S. dollars per barrel, obtained from the IMF International Financial Statistics (IFS) (See Table: 3.1).

The beginning of data period for this study has been selected based on data availability for all series in addition to avoid a great period of price as well as economic and political instability from 1975 until the end of 1981. On the other hand, the end period was based on the latest data point available at the time of the analysis being written. The sample period covers the most recent macroeconomic, crude oil and commodity price shocks as well as price collapses within

[9] For more details on the construction of this index, please see Kilian [2009]

the past thirty years. This way, our study ensures significant variability in the observations to estimate the dynamic fluctuations between macroeconomic factors, world crude oil and maize prices. However, this very same feature presents a significant challenge to the modelling techniques since we will have to incorporate in the empirical estimation a significant number of unstability periods typical of commodity price series (Figure 2-1 and 2-2).

Figure 2-1: *Commodity prices and macroeconomic series in levels.*

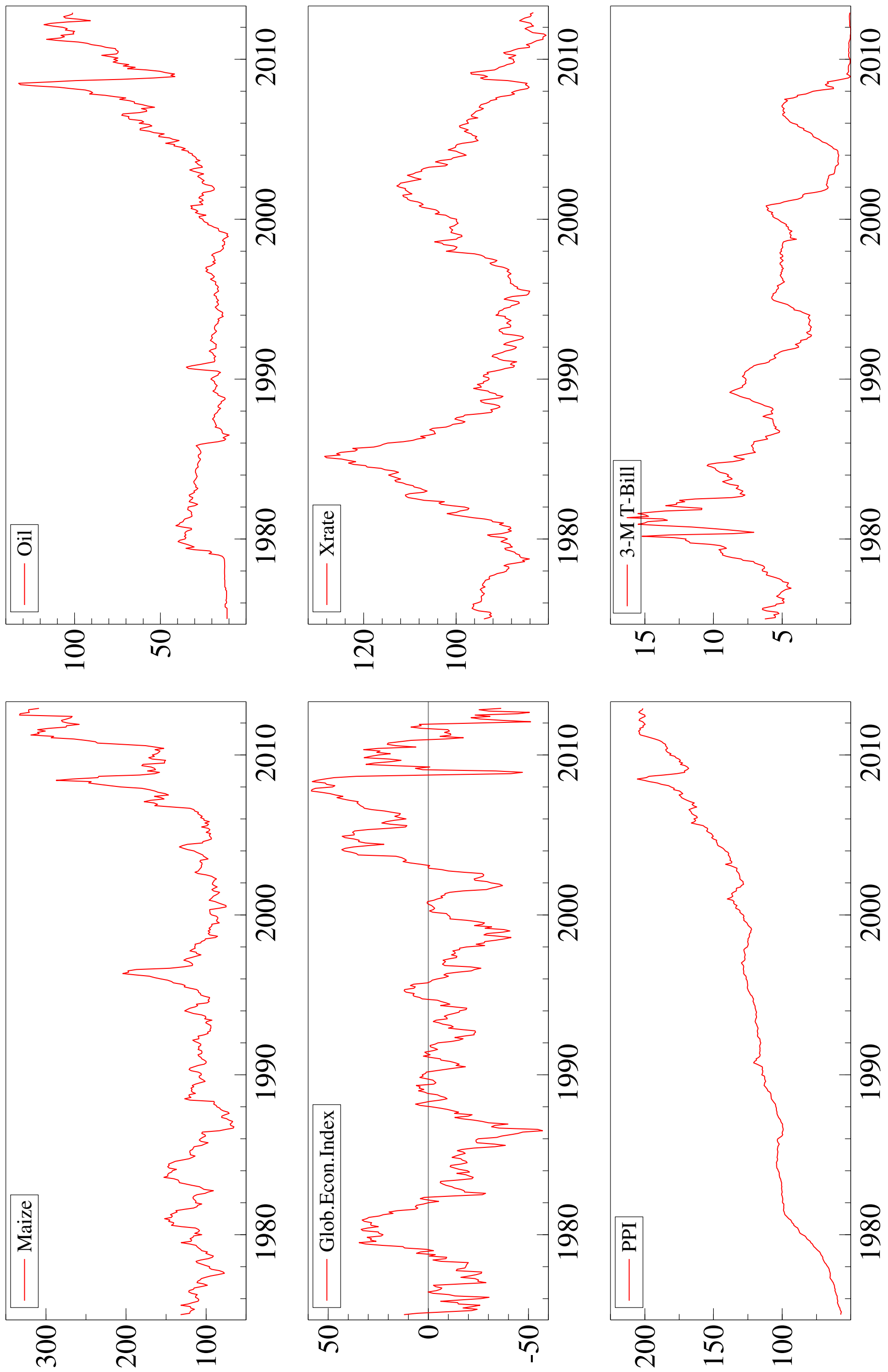
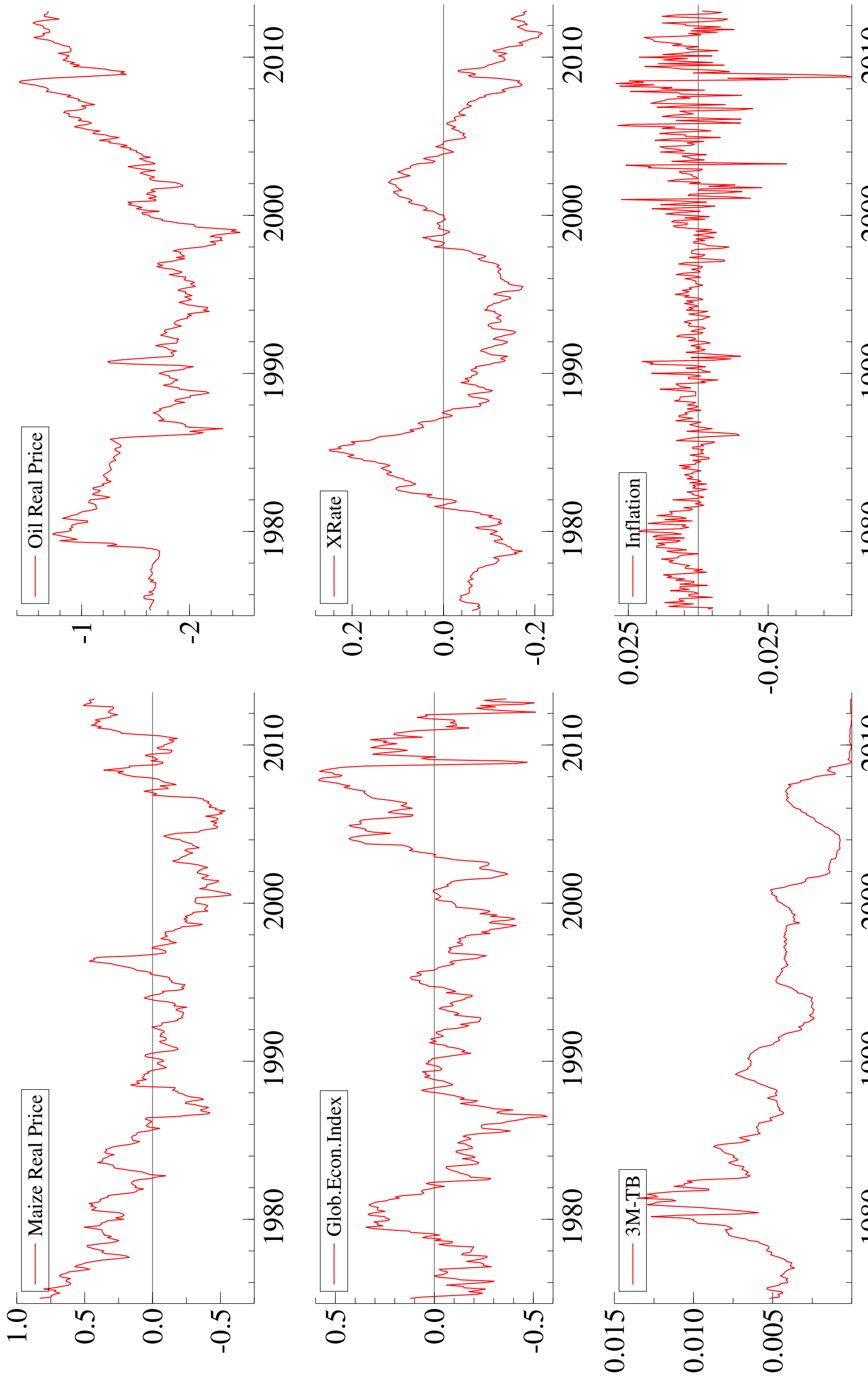


Figure 2-2: *Logarithm of real commodity prices and transformed macroeconomic series.*



In this analysis, all price series have been deflated by diving each of them by the PPI series and subsequently taken the natural logarithms. Also, the monthly inflation rate has been calculated by taking the natural logarithms of PPI and subtracting the current value with that from the previous period (i.e. $\Delta p_t = ln(PPI_t) - ln(PPI_{t-1})$). On the other hand, the short term interest rate has been transformed from annual to a monthly base rate by diving the original figures by 1200. It is worth noting that a brief graphical analysis from Figures 2-1 and 2-2 appear to show that these series do not have a long-run deterministic trend or cyclical component across this time period in agreement with the arguments presented in Sarris and Hallam [2006] as well as the apparent non-stationary nature of these commodity series.

Tables 2.2-2.4 (bottom), summarize the univariate analysis for the skewness, kurtosis, normality and ARCH effects of all variables (already deflated) in each system. From these tables, it is evident that all variables show signs of skewness (both positive and negative skewness) and kurtosis. In the case of maize and crude oil, high values of positive skewness imply that there are very high positive spikes (i.e. upward movements in price) which are rarely matched with downward movements in the price of these commodities. Also, from Tables 2.2-2.4 the calculated values for kurtosis indicate all of these series suffer from thicker tails than a normal distribution. As a result, not surprisingly, test for normality is rejected for all six variables. These are some characteristics of the data which will have to be considered in the specification of the model since it can lead to violations of the assumptions of the statistical model and consequently unreliable estimates..

Table 2.2: *Diagnostic statistics for Model 1 (Maize) on the unrestricted VAR($k = 3$) and empirical VAR ($k = 2$).*

	Multivariate Analysis	
	Unrestricted VAR ($k = 3$)	**Empirical VAR** ($k = 2$)
Tests for Autocorrelation:		
LM(1):	$\chi^2(36) = 37.25$	$\chi^2(16) = 23.20$
LM(2):	$\chi^2(36) = 48.46^{*}$	$\chi^2(16) = 22.47$
Test for Normality:	$\chi^2(12) = 712.83^{\ddagger}$	$\chi^2(8) = 156.68^{\ddagger}$
Test for ARCH:		
LM(1):	$\chi^2(441) = 972.23^{\ddagger}$	$\chi^2(100) = 310.41^{\ddagger}$
LM(2):	$\chi^2(882) = 1688.63^{\ddagger}$	$\chi^2(200) = 459.48^{\ddagger}$

	Univariate Analysis							
	ARCH[1]		**Normality**[2]		**Skewness**		**Kurtosis**	
Variables	U. VAR ($k = 3$)	E. VAR ($k = 2$)	U. VAR ($k = 3$)	E. VAR ($k = 2$)	U. VAR ($k = 3$)	E. VAR ($k = 2$)	U. VAR ($k = 3$)	E. VAR ($k = 2$)
Δmz_t	3.02	$6.39^{\dagger}$	$107.38^{\ddagger}$	$7.98^{\dagger}$	0.41	0.01	7.02	3.69
Δo_t	$15.54^{\ddagger}$	$30.61^{\ddagger}$	$55.15^{\ddagger}$	$7.14^{\dagger}$	0.23	-0.24	5.40	3.58
Δy_t	$27.17^{\ddagger}$	$29.44^{\ddagger}$	$194.34^{\ddagger}$	$49.72^{\ddagger}$	-0.64	0.01	9.72	5.15
$\Delta^2 p_t$	$42.31^{\ddagger}$	$49.30^{\ddagger}$	$128.67^{\ddagger}$	$69.94^{\ddagger}$	-0.82	-0.17	8.11	5.75
Δi_t	$53.78^{\ddagger}$		$171.20^{\ddagger}$		-1.89		17.45	
Δxr_t	1.57		$16.85^{\ddagger}$		0.31		4.14	

Notes: Significance at the the 1%, 5% and 10% level are denoted by $^{(\ddagger)}$, $^{(\dagger)}$ and $^{(*)}$ respectively.

[1] ARCH (k) is a test for autoregressive heteroskedasticity approximately distributed as $\chi^2(3)$ for the unrestricted VAR and $\chi^2(2)$ for the empirical VAR.

[2] Is the Doornik and Hansen [2008] test for univariate normality distributed as $\chi^2(2)$.

Table 2.3: *Diagnostic statistics for Model 2 (Soybean) on the unrestricted VAR($k=3$) and empirical VAR ($k=2$).*

	Multivariate Analysis	
	Unrestricted VAR ($k=3$)	**Empirical VAR ($k=2$)**
Tests for Autocorrelation:		
LM(1):	$\chi^2(36) = 37.23$	$\chi^2(16) = 21.27$
LM(2):	$\chi^2(36) = 50.38^{*}$	$\chi^2(16) = 25.80$
Test for Normality:	$\chi^2(12) = 680.93^{\ddagger}$	$\chi^2(8) = 178.90^{\ddagger}$
Test for ARCH:		
LM(1):	$\chi^2(441) = 1025.51^{\ddagger}$	$\chi^2(100) = 391.92^{\ddagger}$
LM(2):	$\chi^2(882) = 1694.61^{\ddagger}$	$\chi^2(200) = 564.34^{\ddagger}$

	Univariate Analysis							
	ARCH[1]		**Normality[2]**		**Skewness**		**Kurtosis**	
Variables	U. VAR ($k=3$)	E. VAR ($k=2$)	U. VAR ($k=3$)	E. VAR ($k=2$)	U. VAR ($k=3$)	E. VAR ($k=2$)	U. VAR ($k=3$)	E. VAR ($k=2$)
Δsb_t	3.51	0.542	$57.43^{\ddagger}$	$7.59^{\dagger}$	0.66	0.21	6.16	3.64
Δo_t	$14.44^{\ddagger}$	$43.97^{\ddagger}$	$55.00^{\ddagger}$	$7.73^{\dagger}$	0.23	-0.28	5.40	3.60
Δy_t	$26.50^{\ddagger}$	$27.66^{\ddagger}$	$198.13^{\ddagger}$	$60.98^{\ddagger}$	-0.64	0.13	9.72	5.15
$\Delta^2 p_t$	$49.53^{\ddagger}$	$31.42^{\ddagger}$	$118.01^{\ddagger}$	$82.50^{\ddagger}$	-0.82	-0.29	8.11	6.20
Δi_t	$54.67^{\ddagger}$		$168.30^{\ddagger}$		-1.89		17.45	
Δxr_t	1.57		$16.93^{\ddagger}$		0.31		4.14	

Notes: Significance at the the 1%, 5% and 10% level are denoted by $^{(\ddagger)}$, $^{(\dagger)}$ and $^{(*)}$ respectively.

[1] ARCH (k) is a test for autoregressive heteroskedasticity approximately distributed as $\chi^2(3)$ for the unrestricted VAR and $\chi^2(2)$ for the empirical VAR.

[2] Is the Doornik and Hansen [2008] test for univariate normality distributed as $\chi^2(2)$.

Table 2.4: *Diagnostic statistics for Model 3 (Sugar) on the unrestricted VAR($k=3$) and empirical VAR ($k=2$).*

	Multivariate Analysis	
	Unrestricted VAR ($k=3$)	**Empirical VAR ($k=2$)**
Tests for Autocorrelation:		
LM(1):	$\chi^2(36) = 31.30$	$\chi^2(16) = 22.44$
LM(2):	$\chi^2(36) = 41.29$	$\chi^2(16) = 23.70$
Test for Normality:	$\chi^2(12) = 611.75^{\ddagger}$	$\chi^2(8) = 277.59^{\ddagger}$
Test for ARCH:		
LM(1):	$\chi^2(441) = 1031.26^{\ddagger}$	$\chi^2(100) = 381.80^{\ddagger}$
LM(2):	$\chi^2(882) = 1636.77^{\ddagger}$	$\chi^2(200) = 528.86^{\ddagger}$

	Univariate Analysis							
	ARCH[1]		**Normality**[2]		**Skewness**		**Kurtosis**	
Variables	U. VAR ($k=3$)	E. VAR ($k=2$)	U. VAR ($k=3$)	E. VAR ($k=2$)	U. VAR ($k=3$)	E. VAR ($k=2$)	U. VAR ($k=3$)	E. VAR ($k=2$)
Δs_t	4.10	1.89	$12.90^{\ddagger}$	4.67^{*}	0.14	0.04	3.93	3.49
Δo_t	$12.84^{\ddagger}$	$30.67^{\ddagger}$	$50.40^{\ddagger}$	$5.77^{\dagger}$	0.25	-0.14	5.28	3.54
Δy_t	$29.60^{\ddagger}$	$33.46^{\ddagger}$	$197.66^{\ddagger}$	$128.64^{\ddagger}$	-0.64	-0.36	9.83	7.43
$\Delta^2 p_t$	$51.60^{\ddagger}$	$35.86^{\ddagger}$	$100.81^{\ddagger}$	$100.94^{\ddagger}$	-1.03	-0.62	8.89	7.36
Δi_t	$56.02^{\ddagger}$		$181.08^{\ddagger}$		-1.70		16.18	
Δxr_t	1.33		$15.38^{\ddagger}$		0.29		4.06	

Notes: Significance at the the 1%, 5% and 10% level are denoted by $^{(\ddagger)}$, $^{(\dagger)}$ and $^{(*)}$ respectively.

[1] ARCH (k) is a test for autoregressive heteroskedasticity approximately distributed as $\chi^2(3)$ for the unrestricted VAR and $\chi^2(2)$ for the empirical VAR.

[2] Is the Doornik and Hansen [2008] test for univariate normality distributed as $\chi^2(2)$.

2.5 Empirical Analysis

In order to derive the full-information maximum likelihood (FIML) estimator it is required an explicit probability formulation of the initial estimated VAR model. Consequently, in estimating the model we assume multivariate normality (e.g. Homoscedasticity and no significant serial autocorrelation in the residual errors.). In case the model is unable to fulfill these assumptions we may be not able to provide any conclusive evidence since the parameter estimates are based on an incorrectly derived estimator. Consequently it is essential that in order "to claim that conclusions are based on FIML inference is to claim that the empirical model is capable of accounting for all the systematic information in the data in a satisfactory way" [Juselius, 2006].

In our study, we are interested in estimating three models corresponding to each commodity of interest (i.e. Maize, Soybeans and Sugar). Our empirical analysis begins by defining the three models of interest and subsequently estimating all three unrestricted VAR (UVAR) models. Then, we conduct a series of analysis in order to find a well-specified empirical model. Once we have statistical well-specified models, we proceed to test for the rank and stability of the system. Finally, we proceed to identify the long-run relations by a conducting a series of theoretical and empirical restrictions in the equations of interest.

The initial three unrestricted models consist of six variables each ($p = 6$) in the following form:

$$X'_{1,t} = [mz_t, o_t, y_t, xr_t, i_t, \Delta p_t]' \; - \; \text{Maize}$$
$$X'_{2,t} = [sb_t, o_t, y_t, xr_t, i_t, \Delta p_t]' \; - \; \text{Soybean}$$
$$X'_{3,t} = [s_t, o_t, y_t, xr_t, i_t, \Delta p_t]' \; - \; \text{Sugar}$$

where mz_t, sb_t, s_t,o_t, y_t, xr_t and i_t are the logarithm prices of maize, soybeans, sugar, crude oil, the Kilian index of global economic activity, real exchange rate, nominal interest rate and inflation rate[10]. For each of the three models, the initial number of lags has been selected to three (i.e. $k = 3$) by minimizing the standard Schwarz (SC) and Hanna-Quinn (HQ) information criteria as well as based on the model misspecification of 'no serial autocorrelation' on the first and k^{th} lag. Additionally, since none of the series present linear trends (at least not until the very end of the sample), we assume that the only deterministic component in all three models are the intercepts, which have been restricted to the cointegrating space. In general, the estimated unrestricted VECM (UVECM) of order $k-1$ with the six variables ($p = 6$) of interest can be written in matrix form as:

$$\begin{bmatrix} \Delta\{mz, sb, s\}_t \\ \Delta o_t \\ \Delta y_t \\ \Delta^2 p_t \\ \Delta xr_t \\ \Delta i_t \end{bmatrix} = \sum_{i=1}^{k-1} \Gamma_i \begin{bmatrix} \Delta\{mz, sb, s\}_{t-1} \\ \Delta o_{t-1} \\ \Delta y_{t-1} \\ \Delta^2 p_{t-1} \\ \Delta xr_{t-1} \\ \Delta i_{t-1} \end{bmatrix} + \alpha\beta' \begin{bmatrix} \{mz, sb, s\}_{t-1} \\ o_{t-1} \\ y_{t-1} \\ \Delta p_{t-1} \\ xr_{t-1} \\ i_{t-1} \end{bmatrix} + \Phi_1 \begin{bmatrix} D_{t,1} \\ \vdots \\ D_{t,d} \\ 1 \end{bmatrix} + \varepsilon_t \tag{2.2}$$

where α is a $p \times r$ and β' is an $r \times p$ matrix with $r \leq p$ vector of stationary cointegrating relations[11].

[10]All prices have been deflated using the price level as previously described.

[11]In the case of $r = n$, then Π is a singular matrix and we can model all variables as stationary; Φ_1 is a matrix of $p \times d$, where d is the number of intervention dummies in addition

According to Juselius [2006], any misspecification of the model assumption will have fundamental effects on the parameters estimates and interpretation from the model. Therefore, it is essential to apply misspecification tests that provide light of the model constancy and normality of the residuals as assumed in the VAR model. The unrestricted model for all three commodities present a number of misspecifications, which are primarily derived from the non-normality of the residuals in addition to ARCH effects (See Table 2.2, 2.3 and 2.3). The hypothesis of normality of the residuals for each individual variable is also rejected for most cases due to primarily the excess skewness and kurtosis the variables present. Nevertheless, Juselius [2006] argues that one can achieve a well statistically specified model by modifying some of the initial specifications of the UVAR using the following structure:

- including intervention dummies to account for significant political or institutional changes;
- conditioning on weakly exogenous variables;
- splitting or changing the sample period;
- checking the information set by adding new variables;
- examining the parameter constancy of the model (e.g. structural shifts in the model parameters);
- checking the adequacy of the measurements of the chosen variables;
- increasing the lag length.

In an effort to achieve a well-specified model, the first step we take is to detect periods of instability and structural changes in individual series by detecting those residuals larger than three standard deviations ($\pm\ 3\hat{\sigma}$). Table 2.5 provides a list of intervention dummies structural shifts that have been detected and has helped

to the constant.

define a well specified VAR model for all three specification models. The periods of instability here detected coincide with major price fluctuations in commodity markets from the early 80's and early 2000's, monetary policy interventions (e.g. expansion the Federal Reserve Bank of the U.S. in 2003) as well as macroeconomic instability related to the recent global financial crisis of 2007/08 to the present.

Another possible source of misspecification is the inclusion of weakly exogenous variables in the models. Weakly exogenous variables do not have a long-run effect in the variables of interest and therefore tests should be performed in order to identify these variables. In Table 2.6 we present the tests for weakly exogenous variables for all possible rank selections. From the test, we conlcude that, for all possible rank (in all three specifications) the real exchange rate and the nominal short-run interest rate appear to be weakly exogenous. Although, test results from for 'Maize' are not as determinant as it is the case on the other two models, we argue that in the first place we do not expect these variables to have a long-run effect in the agricultural commodities and also there is no reason to believe the system contains more than three cointegrating vectors. Thus, we focus the analysis and in the evidence presented in the test results related to a rank less than four. For this reason, we condition both, the real exchange rate and nominal short-run interest rate, to be weakly exogenous in the model and thus to remain outside the cointegrating space.

Table 2.5: *Description of intervention dummies.*

Date: Year	Date: Month	Type	Events	Oil	Maize	Soy-beans	Sugar	Inflation	Kilian Index
1983	May	Transitory	Drought in South Africa & Frost in Cuba				✓		
1983	August	Transitory	Drought Midwest U.S.			✓			
1986	February	Transitory	Collapse of Oil Prices	✓					
1988	June	Transitory	Drought Midwest U.S.		✓	✓			
1990	August	Transitory	Gulf War	✓					
1993	July	Transitory	Flooding Midwest U.S.			✓			
1996	Sept.	Transitory	Drought Midwest U.S.		✓				
2003	April	Level Shift	Peak U.S. Monetary Policy		✓				
2004	August	Level Shift	U.S. Monetary Policy			✓			
2008	June	Transitory	2007/08 commodity shock		✓				
2008	August	Transitory	Financial Crisis 2008					✓	
2009	January	Transitory	Financial Crisis 2008						✓
2012	January	Transitory	Eurozone Debt Crisis						✓
2012	July	Transitory	Drought Midwest U.S.		✓				

Table 2.6: *Test of Weak Exogeneity.*

Model 1 - Maize

Rank	5% C.V.	mz_t	o_t	y_t	Δp_t	xr_t	i_t
1	3.841	2.655	0.155	7.575	83.203	0.565	0.000
2	5.991	7.146	7.426	20.000	104.543	5.521	4.011
3	7.815	10.228	10.706	34.094	114.159	5.654	7.322
4	9.488	13.191	11.013	38.394	115.385	5.654	11.190
5	11.070	16.707	12.722	41.870	118.324	7.601	15.019

Model 2 - Soybean

	sb_t	o_t	y_t	Δp_t	xr_t	i_t	
1	3.841	2.613	88.546	6.126	0.280	0.501	0.367
2	5.991	5.713	99.262	8.558	5.929	4.217	3.804
3	7.815	5.928	105.308	16.573	8.177	4.265	4.461
4	9.488	11.105	110.439	21.834	11.837	5.746	4.695
5	11.070	15.652	113.066	25.762	11.847	9.106	8.601

Model 3 - Sugar

	s_t	o_t	y_t	Δp_t	xr_t	i_t	
1	3.841	0.343	119.285	5.298	1.686	0.710	0.498
2	5.991	15.762	120.214	5.325	1.687	1.298	1.035
3	7.815	19.732	123.252	12.465	1.748	1.300	1.125
4	9.488	25.620	128.403	18.237	3.319	3.943	3.298
5	11.070	28.547	128.409	21.039	3.585	8.000	6.816

After determining possible weakly exogenous variables and considering extraordinary events (as intervention dummies) in the models, the distributions of the residuals become closer to a normal distribution than in the initial estimated model. In Tables 2.2-2.4 we show evidence that the empirical VAR (EVAR) do not suffer from any serial autocorrelation and individual variables signs of non-normality have significantly improved from the unrestricted model. Even though in Tables 2.2-2.4 the models present signs of non-normality in the residuals, this is primarily due to the excess kurtosis, which none of these present a threat to the properties of the estimates [Juselius, 2006]. Therefore, the preferred specified models, shown in these tables, consist of VAR($k = 2$, $p = 4$) with interventions dummies and structural shifts as specified above as well as considering the real exchange rate and nominal short-run interest rate as weakly exogenous in the model with the intercept as the only deterministic component. As before, we can rewrite the EVECM as:

$$\begin{bmatrix} \Delta\{mz, sb, s\}_t \\ \Delta o_t \\ \Delta y_t \\ \Delta^2 p_t \end{bmatrix} = \Gamma_1 \begin{bmatrix} \Delta\{mz, sb, s\}_{t-1} \\ \Delta o_{t-1} \\ \Delta y_{t-1} \\ \Delta^2 p_{t-1} \\ \Delta xr_{t-1} \\ \Delta i_{t-1} \end{bmatrix} + \alpha\beta' \begin{bmatrix} \{mz, sb, s\}_{t-1} \\ o_{t-1} \\ y_{t-1} \\ \Delta p_{t-1} \\ xr_{t-1} \\ i_{t-1} \\ \{D_{s_{0403}}, D_{s_{0804}}\}_{t-1} \end{bmatrix} + \mathbf{A}_1 \begin{bmatrix} \Delta xr_t \\ \Delta i_t \end{bmatrix} + \Phi_1 \begin{bmatrix} D_{t,1} \\ \vdots \\ D_{t,d} \\ \{\Delta D_{s_{0403}}, \Delta D_{s_{0804}}\}_t \\ 1 \end{bmatrix} + \begin{bmatrix} \hat{\varepsilon}_{\{mz,sb,s\},t} \\ \hat{\varepsilon}_{o,t} \\ \hat{\varepsilon}_{y,t} \\ \hat{\varepsilon}_{\Delta p,t} \end{bmatrix} \tag{2.3}$$

where in this case, the CVAR system contains four variables ($p = 4$) and as before Γ_1 is a $p \times 6$, α is a $p \times r$ matrix while β' is $r \times 7$[12] with $r \leq p$ vector of stationary cointegrating relations and the real exchange rate and nominal short-

[12]From Equation 2.3, β' is $r \times 7$ matrix for both Maize and Soybean specifications while for Sugar, β' is $r \times 6$ since we have not determined any shift in the cointegrating space. $\mathbf{A}_1$ has dimensions of $p \times m$, where m corresponds to the number of weakly exogenous variables in the system (two in this case).

run interest rate restricted as weakly exogenous.

Thus, the three models we empirically test are those associated with our preferred specifications described in Equation 2.3. In this case, each system has a constant restricted to the cointegrating space, in addition to the two weakly exogenous variables (i_t and $\Delta^2 p_t$), a series of intervention dummies outlined in Table 2.5 with no shift dummy for the specification associated with Model 3 (Sugar) and including the shift dummy for April 2003 (for Model 1- Maize) as well as a shift dummy for August 2004 (for Model 2-Soybean).

2.5.1 Determining the rank.

According to Juselius [2006], once we have identified a well-specified empirical model then we we can test for the rank of the system. We proceeded to test the rank for each and one of the models specified empirical models as in Equation 2.3. In determining the choice of the cointegrating rank we have considered: (1) the trace test for cointegrating rank; (2) the critical values of the α coefficients; (3) the recursive graphs of the trace statistic; (4) the graphs of the cointegrating relations as well as the economic interpretability of each system.

In Table 2.7 we present a summary of the rank test for all three models. It is important to note that in all three cases we have used the Bartlett trace test corrected for small sample behaviour and dummies as proposed by Johansen [2000, 2002]. The top of Table 2.7 presents the rank test conducted for Maize where we are able to reject the null hypothesis of one and two unit roots (at the 10% level) and fail to reject three unit roots in the system. Thus, concluding that for the system including Maize (as one of the agricultural commodity price) we have three cointegrating relationships, which is consistent with the equations associated with the price level, global economic activity and that of maize in terms of macroeconomic variables and crude oil prices[13]. On the other hand, Soybean from Table 2.7, corresponds to the specification related to the relationship between Soybeans, crude oil and the macroeconomic where we fail to reject two unit roots (at the 10% level) in the system. For Soybean, we conclude that we have two cointegrating relationships, which is consistent with that equation of Soybeans, oil prices and macroeconomic variables and the price level. The third and last model tested is that which corresponds to Sugar, crude oil and the same macroeconomic variables used before. From Table 2.7, the rank test indicates that we cannot reject the null hypothesis of 3 unit roots at the 10% level. Consequently, we conclude that for Sugar we have a total of three possible cointegrating relationships.

2.5.2 Stability of the system.

After choosing the rank in the system we want to check the constancy of the estimated long-run parameters [Juselius, 2006]. The parameter constancy of the long-run parameters β can be tested by the 'Max Test for Constancy of β' by applying the Hansen and Johansen [1999] procedure and shown in Figure 2-3. This is a recursive test, which consists of comparing the likelihood ratio test with that of the likelihood function from each sub-sample with the restriction that the cointegration vectors estimated from the full sample fall within the space spanned by the estimated long-run vectors. The test statistic is χ^2 distributed with $p-r$ and r degrees of freedom.

Figure 2-3a shows the constancy test of the slope coefficients for Maize. In

[13] This hypothesis is later tested and results will be presented.

Table 2.7: *The I(1) rank analysis for all models based on the simulated critical values.*

Model 1 - Maize				
Rank	*Trace*	$Trace_{Bart.}$	$C_{.95}$	P-*Value*
$r = 0$	223.228	218.247	71.302	$0.000^{(\ddagger)}$
$r \leq 1$	67.613	66.187	48.621	$0.000^{(\ddagger)}$
$r \leq 2$	28.482	27.815	30.667	$0.095^{(*)}$
$r \leq 3$	6.193	6.058	15.039	0.638
Model 2 - Soybean				
$r = 0$	195.005	190.718	71.550	$0.000^{(\ddagger)}$
$r \leq 1$	51.255	50.209	48.556	$0.034^{(\dagger)}$
$r \leq 2$	27.024	26.053	29.738	0.133
$r \leq 3$	7.616	7.349	14.984	0.494
Model 3 - Sugar				
$r = 0$	211.461	207.012	53.358	$0.000^{(\ddagger)}$
$r \leq 1$	54.933	53.863	35.371	$0.000^{(\ddagger)}$
$r \leq 2$	21.196	20.760	20.874	$0.047^{(\dagger)}$
$r \leq 3$	2.529	2.451	8.327	0.707

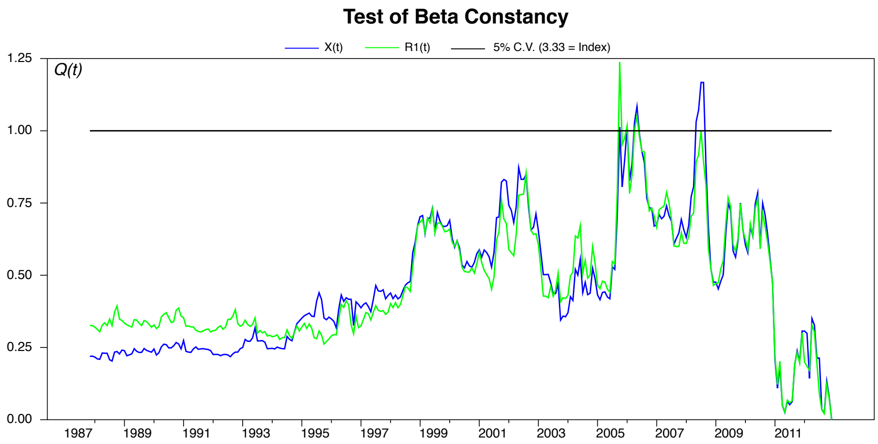
Notes: Simulated Rank Test distribution. Significance at the the 1%, 5% and 10% level are denoted by $^{(\ddagger)}$, $^{(\dagger)}$ and $^{(*)}$ respectively.

this case the constancy test is safely below the rejection area for most of the sample period, except for the period between late 2006 and early 2007, which clearly coincides with the early part of the century commodity price instability and speculation. However, it is evident that even during the period of instability the relationship returns to safe levels below the rejection area of constancy. This is a strong evidence showing that even though there was significant instability during this period the long-run constancy of the parameters did not permanently changed. Additionally, there exists another period of similar short-run rejection of constancy in the long-run parameters, which coincides with the period of great macroeconomic volatility due to the great recession in late 2008. In summary, the R-form[14], which contains both short and long-run information is the only one that appears to present periods of relative instability in the periods before men-

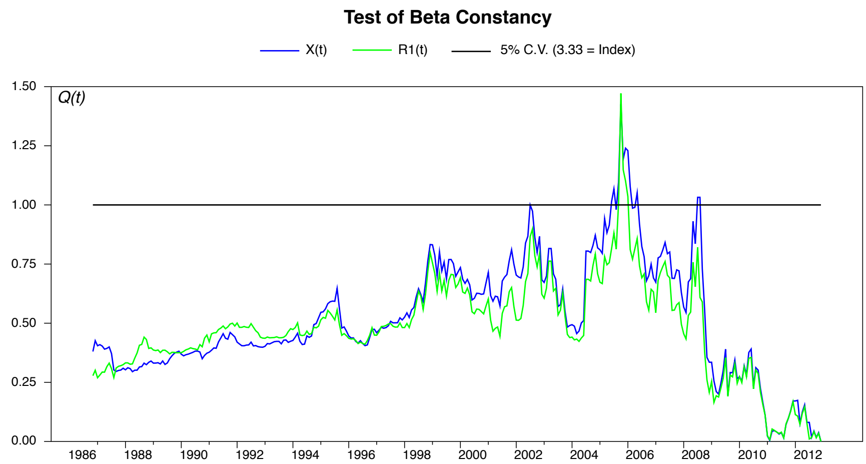
[14]This form contains both the short and long-run dynamics of the parameter stability.

tioned. Nevertheless, soon after it appears that the system returns back to its long-run equilibrium. After this analysis there exists very little evidence that the instability period experienced in the 2006/2007 commodity price market did not permanently affect the long-run parameters of the maize, crude oils prices and macroeconomic variables. Therefore, the recursive constancy parameter presents strong evidence in favor of constant long-run parameters in the cointegrating relationship of maize and crude oil prices and the remaining macroeconomic variables.

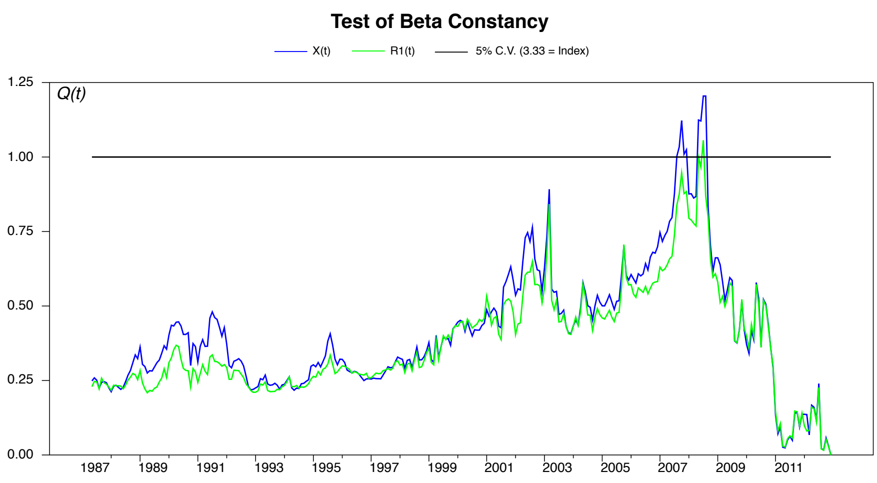
Figure 2-3: *Recursive of constancy tests. The max test of β constancy.*



(a) *Model 1 - Maize*



(b) *Model 2 - Soybean*



(c) *Model 3 - Sugar*

Figure 2-3b shows the The parameter constancy of the long-run parameters β for the soybean relationship. As in the case for maize, also for soybean the constancy test is safely below the rejection area for most of the sample period, except for the period between late 2006 and early 2007, which clearly coincides with the early part of the century commodity price instability and speculation. Also, the long-run parameters present, as expected, instability around the peak of the commodity price boom, but soon returning to levels below the rejection area before showing another period of instability associated with the financial crisis of 2008 before returning to levels well safe below the rejection line. In this case, soybean presents temporary instability periods around late 2002 and early 2003, which could be associated with the monetary expansion that the U.S. employed during this period. In both models for Maize and Soybeans, the long-run parameters present similar periods of instability, which essentially differ by as much as for a few months from those previously highlighted. This is consistent with the literature which highlights that the peaks in the individual commodity price shock occurred not all at the same time [Gilbert, 2010, Headey and Fan, 2008]. At the same time, these periods show evidence of great deal of temporary instability along recent events alone, but in general the relationship appears to be provide signs of stability by the end of the sample. Thus, the recursive parameter test shows that the cointegrating relationship here estimated of long-run parameters constancy despite the periods of instability described.

Figure 2-3c shows the The parameter constancy of the long-run parameters β for the model associated with world sugar prices. As in the case for maize, also for soybean the constancy test is safely below the rejection area for most of the sample period, except for the period between late 2007 and early 2008, which coincides with the period of instability associated with the financial crisis of 2008 before returning to levels well safe below the rejection line. Sugar long-run parameters, as supposed to maize and soybeans, did not suffered from much of the instability during the same period of time. Nevertheless, as in the previous cases the recursive parameter test shows that cointegrating relationship for sugar also presents long-run constant parameters.

2.5.3 Long-Run estimates for Models 1-3

In this section, we are going to impose restriction on the empirical specifications for each an one of the models of interest in order to identify the long-run structure of the system. As suggested by Juselius [2006], we can use two approaches in order to obtain a correct identification: (1) We can impose just-identifying restrictions on the β vectors and subsequently we impose further restrictions by restricting insignificant coefficients in β; (2) We can also test the theoretical relations searching for an identified structure by combining stationary theoretical relations.

Recall that for Maize we have determined as the empirical VAR specification as a VAR(2) model with $r = 3$. That is, we have identified in this model three cointegrating relationships. We proceed to impose restrictions on the long-run parameters in order to identify each cointegrating equation and interpret its economic meaning. In our case, we suspect from previous analysis that inflation (Δp_t) appears to be stationary and together with the index of global economic activity (y_t)[15] represent the first and second stationary relationships. The third cointegrating relationship is suspected to be that of interest, which consists of the real price of Maize (mz_t) explained by fluctuations in the real price of crude oil (o_t), the real exchange rate (xr_t) and real short-term interest rate ($i_t - \Delta p_t$)

[15] By construction the index of global economic activity is stationary and as such it should be reflected as a stationary relationship with itself or other variables.

as exogenous[16]. From Table 2.8 we can see that we fail to reject LR-test with a p-value of 0.237 and thus conclude that the restrictions imposed correctly identify three cointegrating equations and proceed to analyze the economic meaning of these long-run relationships.

Table 2.8: *Model 1 (Maize) - Identified long-run structures (t-statistics in brackets).*

Model 1 - Maize								
	mz_t	Δp_t	y_t	o_t	xr_t	i_t	Ds_{2003}	μ_0
$\hat{\beta}_1$	0.000 [NA]	1.000 [NA]	0.000 [NA]	0.000 [NA]	0.000 [NA]	0.000 [NA]	0.000 [NA]	−0.002 [−3.301]
$\hat{\beta}_2$	0.000 [NA]	0.000 [NA]	1.000 [NA]	0.317 [3.588]	0.000 [NA]	0.000 [NA]	−0.490 [−5.525]	0.676 [4.227]
$\hat{\beta}_3$	1.000 [NA]	38.621 [5.382]	0.000 [NA]	−0.889 [−5.049]	1.415 [2.848]	−38.621 [−5.382]	0.625 [3.428]	−1.341 [−4.305]
	α_1	α_2	α_3					
Δmz_t	0.602 [0.997]	0.010 [0.632]	−0.041 [−3.492]					
$\Delta^2 p_t$	−0.772 [−8.728]	0.004 [1.519]	0.002 [0.935]					
Δy_t	2.376 [3.864]	−0.101 [−6.112]	−0.023 [−1.950]					
Δo_t	−1.506 [−1.759]	−0.002 [−0.097]	0.037 [2.235]					
Test of Restricted Model: $\chi^2(3) = 8.011$ [0.237]								

Table 2.8 show that as suspected the first cointegrating relationship is associated with the stationary nature of the inflation rate. The second linear combination is that of the index of global economic activity, together with real price of crude oil. This equation predicts that real shocks to the crude oil price have a negative impact on the global economic activity index. These results are corroborated in the literature by Kilian [2009] and He et al. [2010]. However, we do not find signs of weak exogeneity between the index of global economic activity and real crude oil prices as suggested by He et al. [2010] and the magnitude and adjustment coefficients of our equation are considerably different their esti-

[16] An I(2) analysis was also conducted in order to corroborate the correct price transformations and no I(2) variables were found in the model given the specification used in this model.

mates. Our estimates indicate that approximately a percentage increase in the world real price of crude oil has a long-run negative impact of about 3% in the global output, with a very low equilibrium towards the long-run relationship of 2% a month. These estimates emphasize the magnitude and long-lasting effects of shocks in the world real energy market on the real economic activity. Moreover, we also find substantial evidence indicating the shift in the level of global output by approximately 50% since 2003, which might explain why a number of authors have blamed the unforeseen global demand as a factor in the commodity price crisis. However, in our case there is no conclusive evidence we can provide supporting this findings.

From Table 2.8, the long-run relationship of interest is that associated with $\hat{\beta}_3$, where the real price of maize is expressed as a function of the remaining variables. In this case, all the coefficients have the expected sign and are highly statistically significant. The estimated long-run coefficient of the real world price of crude oil is estimated to be 0.889, which after testing the null hypothesis of a one-to-one long-run effect we fail to reject at the 1% level with a p-value of 0.727[17]. Therefore, from this analysis we conclude that a one percent increase in the real long-run world price level of crude oil is associated with a one percent increase in the long-run real world price of maize. Looking at the coefficient alone, the implications of this estimate are profound in the Maize-Oil relationship. However, it's important to highlight that the index of global economic activity (aggregate demand) is not included in the cointegrating space. Thus, if the world aggregate demand has a significant impact on the real world price of crude oil, then it is likely estimating a mixture of effects coming from from the demand side of economy as well as the crude oil market. In order to understand

[17]The test corresponds to a $\chi^2(7) = 4.447$.

the extent to which shocks to real crude oil prices on Maize, further statistical analysis will be presented ahead.

In addition, also from Table 2.8, as the U.S. dollars appreciates with respect to major currencies, it is estimated to have a negative impact in the long-run real price of maize. This finding falls within our expectations since we (and other authors) have argued the possibility that in the long-run as the index of U.S. dollar with major currencies appreciates with respect to major currencies, the real price of maize (USD/ton) decreases with respect to these currencies. Furthermore, we are able to accept the long-run homogeneity between inflation and the nominal short-run interest rate (i.e. the real interest rate). This finding implies that increases to the real interest rate have a negative and significant impact on the real price of maize. This finding reflects the trade-off between the returns to capital to investment from holding commodities. On the other hand, the index for global economic activity (as a proxy for the world business cycles) appears to have no effect in the long-run real price of maize. This finding is somewhat surprising since the index for global economic activity is thought to be a proxy for the world business cycles and increasing aggregate demand would in theory have a positive effect in the long-run real price of maize. However, it is possible that the way in which this variable has been constructed and detrended does not necessarily corresponds to that variation associate with the commodity market of maize rather. Finally, our estimates show that since April 2003, the real price of maize has increased in real terms by approximately 63% compared to the entire previous period, which is a substantial increase considering this has occurred in a lapse of eight years or less.

The second area of interest in that of the speed of adjustment towards the equilibrium (α coefficients in Table 2.8). By closely examining α_3 in Table 2.8, it shows that all variables, except growth rate of inflation ($\Delta^2 p_t$) are adjusting forces towards the long-run equilibrium of the real price of maize. Moreover, maize itself, appears to be adjusting to its long-run equilibrium at a very slow pase of approximately 4% a month from a disequilibrium state. However, analyzing maize's price adjustment coefficient by itself can be misleading since as it is shown that both oil price is also helping the system towards its long-run equilibrium. Furthermore, these adjustment coefficients are not implausible given the nature of commodity price markets and are very similar to those previously estimated in the literature (see for example Cashin et al. [2004]).

Table 2.9: *Model 2 (Soybeans) - Identified long-run structures (t-statistics in brackets).*

Model 2 - Soybean								
	sb_t	Δp_t	y_t	o_t	xr_t	i_t	Ds_{2004}	μ_0
$\hat{\beta}_1$	0.000 [NA]	1.000 [NA]	−0.007 [−3.440]	0.000 [NA]	0.000 [NA]	0.000 [NA]	0.000 [NA]	−0.002 [−4.562]
$\hat{\beta}_2$	1.000 [NA]	0.000 [NA]	0.000 [NA]	−0.937 [−4.662]	2.089 [3.582]	0.000 [NA]	0.899 [3.925]	−2.223 [−6.268]
	α_1	α_2						
Δsb_t	−0.826 [−2.248]	−0.036 [−3.904]						
$\Delta^2 p_t$	−0.687 [−11.069]	0.001 [0.871]						
Δy_t	1.095 [2.462]	0.013 [1.184]						
Δo_t	−0.265 [−0.447]	0.036 [2.411]						
Test of Restricted Model: $\chi^2(6) = 7.624[0.267]$								

On the other hand, the long-run estimates for the soybean specification are presented in Table 2.9. We determined two cointegrating relationships for this model and similar to Maize, the first relationship is that of inflation and the index for global economic activity. The second cointegrating relationship (that is $\hat{\beta}_2$ from Table 2.9) is that associated with the long-run fluctuations between the real world price of crude oil and macroeconomic variables. The estimated long-run coefficient for the real world price crude oil is 0.937, which implies that approximately a one-to-one relationship between the long-run real world price of soybeans and crude oil. Additionally, we have tested the restriction of a one-to-one long-run relationship between these two variables and we fail to reject the null hypothesis with a p-value of 0.364. Therefore, we cannot reject the hypothesis that in the long-run, an increase in the real world price of crude oil has a one-to-one relationship with the real world price of soybeans. This findings are categorically equivalent to this found for the Maize model in that we cannot attribute solely this effect to the real world price of crude oil, but to a combination of demand and oil market effects. Also from Table 2.9, we obtain similar results as those from the maize relationship. As in the case for maize, also soybeans present a negative relationship between the real exchange rate of the U.S. dollar and major currencies. Additionally, since August 2004 to December 2012, the real world price of soybeans has increased approximately 90% compared to increases in the previous period (1982-2003). In summary, our estimates for the Soybean cointegrating relationship show that the real world price of crude oil, the U.S. exchange rate and the real interest rate are important determinants in the long-run dynamics of its long-run price stability.

Table 2.10: *Model 3 (Sugar) - Identified long-run structures (t-statistics in brackets).*

Model 3 - Sugar							
	s_t	Δp_t	y_t	o_t	xr_t	i_t	C
β_1	1.000 [NA]	0.000 [NA]	0.000 [NA]	0.000 [NA]	2.545 [6.504]	0.000 [NA]	2.690 [62.269]
β_2	0.000 [NA]	1.000 [NA]	0.000 [NA]	0.000 [NA]	0.000 [NA]	0.000 [NA]	−0.002 [−4.395]
β_3	0.000 [NA]	0.000 [NA]	1.000 [NA]	0.000 [NA]	0.000 [NA]	0.000 [NA]	0.000 [NA]
	α_1	α_2	α_3				
Δs_t	−0.096 [−5.660]	0.366 [0.567]	−0.005 [−0.280]				
$\Delta^2 p_t$	0.001 [0.701]	−0.764 [−12.300]	0.004 [2.359]				
Δy_t	−0.014 [−1.189]	1.352 [3.098]	−0.061 [−4.687]				
Δo_t	−0.006 [−0.423]	−0.750 [−1.315]	0.004 [0.215]				
Test of Restricted Model: $\chi^2(9) = 3.450[0.944]$							

The long-run results for third specification is that shown in Table 2.10. As supposed to the previous two relationships, sugar appears not to have a long-run relationship with crude oil and only the real U.S. exchange rate is the only variable from the model to matter in the long-run world price of sugar dynamics.

2.5.4 Common driving trends

In this section we will try to identify the common stochastic trends of the system. In that sense, for example, we are interested in determining to what extent shocks to the real world price of crude oil have an impact on both Maize and Soybean prices. In the cade of Maize, we have identified three cointegrating relationships and p-r=1 common stochastic trends. From Table 2.11, the common stochastic trends associated with the real world price of Maize are associated with itself and long-run shocks to the real price of crude oil alone. More precisely, permanent shocks to the real price of crude oil have approximately a permanent effect and transmitted to the real price of maize by a factor of 0.67, everything else constant. On the other hand, it appear that inflationary shocks only have a short-run effect in the real world price of maize. In other words, only shocks to the price of crude oil and maize itself have a long-run permanent effect in the price of maize. This is an important conclusion to arrive since the literature on the effects of crude oil prices on agricultural commodities (particularly that of biofuel-commodities) argue that since the early part of the century, and as a consequence of record high prices of oil, agricultural commodities (such as maize) are more susceptible to crude oil price shocks.

Table 2.11: *The MA representation when β is restricted - The Long-Run Impact*

Model 1 - Maize				
	$\hat{\varepsilon}_{mz_t}$	$\hat{\varepsilon}_{\Delta p_t}$	$\hat{\varepsilon}_{y_t}$	$\hat{\varepsilon}_{o_t}$
mz_t	0.571 [3.384]	−0.827 [−1.361]	0.014 [0.075]	0.674 [5.188]
$\Delta^2 p_t$	−0.000 [−3.384]	0.000 [1.361]	−0.000 [−0.075]	−0.000 [−5.188]
y_t	−0.204 [−3.384]	0.295 [1.361]	−0.005 [−0.075]	−0.240 [−5.188]
o_t	0.643 [3.384]	−0.931 [−1.361]	0.015 [0.075]	0.758 [5.188]
Model 2 - Soybean				
	$\hat{\varepsilon}_{sb_t}$	$\hat{\varepsilon}_{\Delta p_t}$	$\hat{\varepsilon}_{y_t}$	$\hat{\varepsilon}_{o_t}$
sb_t	0.690 [3.904]	−0.879 [−1.356]	0.133 [1.788]	0.678 [3.986]
$\Delta^2 p_t$	0.003 [1.853]	0.013 [1.965]	0.011 [13.718]	−0.001 [−0.567]
y_t	0.482 [1.853]	1.875 [1.965]	1.506 [13.718]	−0.142 [−0.567]
o_t	0.737 [3.904]	−0.938 [−1.356]	0.142 [1.788]	0.723 [3.986]

Notes: The magnitude of the coefficients on $\Delta^2 p_t$ is near zero although statistically significant.

In Table 2.11 (bottom), we present the stochastic trends associated with the soybeans specification. Here, we are able to identify two stochastic trends primarily derived from shocks to the real price of crude oil and marginally from the global economic activity. In fact, permanent shocks to real crude oil prices appears to have a permanent effect by a factor of approximately 0.67, which is the same estimated for Maize. Additionally, permanent shocks to the real global economic activity index appears to also have a marginal permanent effect of the world price of soybeans by a factor of approximately 0.13 (at the 10% level).

On the other hand, shocks to inflation and the exchange rate do not appear to have a long-run effect to the real world price of soybeans. Thus, in summary, shocks to crude oil, the global economic activity index and soybeans itself have a permanent effect on the real world price of soybeans.

2.6 Conclusion

This study examines the long-run relationship between the real world price of maize, soybeans and maize with the real world price of crude oil and a series of macroeconomic variables. We apply a cointegration analysis for monthly series from January 1982 until December 2012. The main empirical results support a strong relationship between fundamentals and the world price of Maize and Soybeans. Particularly, we document significant causal long-run relationships between these agricultural commodities with the real world price crude oil, the real interest rate and the real U.S. exchange rate. In fact, we show that in the long-run crude oil prices and these agricultural commodities share a one-to-one relationship. In other words, a one-percent increase in the price of real crude oil has is associated with a one-percent increase in the price of maize and soybeans. Despite the literature suggesting the neutrality between agricultural commodities and energy prices (mainly crude oil) our findings show that a very strong long-run causal relationship between these and macroeconomic factors. Moreover, we find that permanent shocks to crude oil prices are transmitted to both maize and soybeans by a factor of 0.67 for both commodities.Thus, this conclusion suggests that among all the variables here considered, only shocks to the real price of crude oil is permanently transmitted to the real price of maize and soybeans.

In this aspect, our study contradicts the results from Campiche et al. [2007], Yu et al. [2006], Zhang et al. [2009, 2010] where no long-run (or partial) relationship was estimated among these variables. These results emphasize that in order to informative estimate a very complex long-run relationship, as in the case of agricultural commodities, one need to consider long-data series anymore than just one possible factor affecting these price series. In addition, our results show that despite the instability associated with the period between 2007/08, the long-run relationship between crude oil and these agricultural commodities has remained stable during the entire sample period. These results contradicts those found in studies by Ciaian and Kancs [2011a,b], Harri et al. [2009], Natanelov et al. [2011] where instabilities in individual variables are used to model instability in the cointegrating space.

Similarly, our findings suggests that despite the period of instability between 2007/08, the long-run estimated coefficients are stable along the sample period. The only period of instability associated with these relationship is that around the peak of the commodity shock of 2007/08, which provides some evidence confirming the findings by Tang and Xiong [2012a] and Pen and Sevi [2013] that speculation might have played an important role in explaining some of the price increases during this period. Moreover, our results also support that the real interest rate and the U.S. exchange rate are cointegrated with these commodities prices as it was the case in Belke et al. [2014]. Nevertheless, it's only permanent shocks to real crude oil prices that have a permanent effect on these commodity price behavior. Therefore, we can conclude that fundamentals are the important factors (in particular demand factors) are the crucial determinants of the long-run dynamics of both these two agricultural food commodities.

From a policy perspective our results indicate that countries that heavily depend on the import and export of these agricultural commodities need to conscious of the fluctuations in crude oil prices. Particularly this is the case for those countries affected by food and agricultural price inflation, then policy makers need to pay close attention to the developments in the global energy markets in addition to the traditional demand and supply channels. That is, since fluctuations in the U.S. dollar exchange rate are found to explain a significant variation in the long-run of these commodity prices as well as the short-term interest rate. All these factors need to be considered when designing appropriate response to commodity price fluctuations.

CHAPTER 3

INTERDEPENDENCE AMONG MACROECONOMIC FACTORS, CRUDE OIL AND AGRICULTURAL COMMODITY MARKETS

3.1 Introduction

The 2006-08 commodity price shock produced a period of extreme price movements and volatility, which made it difficult to forecast agricultural prices and understand their behaviour. In the previous chapter I analyzed the long-run linkages and transmission mechanisms between the real world oil prices, macroeconomic fundamentals and three agricultural commodity prices. One of the main conclusions was that shocks to the real world price of crude oil have a permanent effect on the real price of maize and soybeans. Although these findings are important in understanding the mechanisms and channels through which long-run commodity prices are affected, there are still important implications yet to be analyzed. A corollary from these findings is that an increase in the causal relationship between energy and food prices can (in principle) be associated with stronger volatility spillovers effects between these prices, which in turn may increase the farmers risk premium and reduce the effectiveness of stabilization policies [Serra, 2011]. Thus, understanding volatility spillovers among these markets is crucial for developing countries that are net importers of these agricultural and energy commodities and equally for those that rely on energy and commodity exports. Moreover, without an adequate understanding of commodity prices, it is very difficult to develop good policies to respond to commodity price fluctuations [Deaton, 1999]. Therefore, it is critical for economists and policy makers to understand the degree to which energy prices stimulate food commodity price volatility and their broader social and economic repercussions.

The link between energy and agricultural commodities is particularly important given the recent developments and policy changes in the energy sector. The oil price surge of the early 2000s spurred a number of alternative and greener energy policies to be implemented. As a consequence, the biofuel production from maize and soybeans substantially increased and arguably a new link emerged between energy and food commodities. The channel through which oil prices can increase food commodity prices is through the mandate of biofuel mix with gasoline. Thus, the increase of crude oil prices can be linked to the increase of maize and soybean prices, which in turn can cause other similar agricultural commodities to also increase since these would now compete for the same limited acreage in the short run. Moreover, there is the higher transportation and production costs associated with increases in the price of crude oil. Moreover, as crude oil price increase monetary policy authorities respond by changing interest rates and this in turn have a profound effect on other investment decisions as well as aggregate demand and as exchange rates.

Over the past fifteen years, the co-movement of commodity prices has received a substantial amount of attention in the literature. The price co-movements in commodity markets is thought to take place because macroeconomic and market fluctuations are common to all commodity prices. In the seminal paper by Pindyck and Rotemberg [1990], they showed that there existed unexplained price co-movement in seven raw commodities, which cannot be accounted for by market and macroeconomic fundamentals. In this case, the authors attributed this residual effects to herd behavior in the financial markets; thus, laying the foundations for to the 'excess co-movement' hypothesis. Nevertheless, the literature has questioned the initial findings from Pindyck and Rotemberg, firstly by Leybourne et al. [1994], then Deb et al. [1996] and subsequently by Cashin et al. [1999] and Ai et al. [2006]. The former, points out the non-stationarity nature of commodity price series and thus the methodological deficiencies in Pindyck and Rotemberg analysis. Therefore, Leybourne et al. [1994] apply a pair-wise co-integration analysis to evaluate Pindyck and Rotemberg's hypothesis and conclude that only in two out fifteen pairs does such a phenomenon occurs. On the other hand, Deb et al. [1996] argued that Pindyck and Rotemberg's analysis suffered from substantial mis-specification in their empirical modeling and showed that their results are sensitive to conditional heteroskedasticity in the commodity price data, and also the model is very likely to suffer from instability during the sample period. Likewise, Cashin et al. [1999] find no evidence of price co-movement across different categories of commodities and only some between commodities in the same category. Similarly, Ai et al. [2006] controled for supply factors in addition to economic fundamentals and concluded that there is no excess co-movement within the agricultural commodity markets.

The period from 2006 to 2008 was one that attracted researcher's attention due to a substantial increase in price levels and volatility in commodity markets. For example, Sumner [2009] points out that the percentage price increase in agricultural commodity markets for this period was the largest in the 140-year history for which U.S. data is available. Similarly, Trujillo-Barrera et al. [2012] showed that historical maize volatility of daily percentage price changes was below 25% before 2006 and since then it has increased to over 40% up to 2011. As a result, the literature has again resumed its interest on the causal links between agricultural commodity and energy markets and economic fundamentals.

Nevertheless, the channels through which volatility in agricultural markets operate are complex to determine and spring from various sources in the economy [Prakash and Gilbert, 2011]. These can vary from external factors such as climate change, globalization and new policies which link them with the energy sector. Additionally, there are intrinsic events affecting the volatility in agricultural markets arising from global business cycles, monetary policy and exchange rate volatility as well as uncertainties in price level variations and accelerating income growth in commodity dependent countries. Consequently, there exists an imperative need to understand the degree to which the volatility of agricultural commodities is vulnerable to shocks derived from these factors. Yet, the current state of the empirical literature is weak in offering substantial evidence on the extent to which the observed volatility in commodity markets is linked to volatility in energy markets and economic fundamentals.

The effects of commodity price volatility can have severe repercussions throughout the economy. For instance, increasing agricultural commodity price volatility is translated into higher costs for managing risks in the form of increasing crop insurance premiums, which in turn translates into higher option premiums and hedging costs for farmers [Wu et al., 2011]. Additionally, as a consequence of the financialization of commodity markets, volatility spillovers from the oil price to agricultural commodity prices can in turn diminish diversification efforts in the financial markets when agricultural and energy prices present any degree of price co-movement [Gardebroek and Hernandez, 2013]. From a macroeconomic point of view, Byrne et al. [2013] explains that the design and effectiveness of stabilization policies are affected by both the volatility and persistence of commodity prices. Moreover, as a consequence of the recent increase in the biofuel production, the increased price volatility in agricultural commodities used biofuels production (e.g. maize, soybeans and sugar) can be transmitted to other agricultural markets. That is, as demand increases for biofuels (as a consequence of the mandates) and assuming that agricultural land is constrained, food production decreases and so increase food prices [Zilberman et al., 2013]. Ultimately, all these effects are reflected in a decrease of welfare in the general population, particularly in the poorest countries, where a higher proportion of income is devoted to food consumption. Therefore, examining the transmission degree to which energy volatility and economic fundamentals stimulate food price volatility is vital for determining the severity of negative impacts on welfare, for both investment and risk management as well as the impact on economic growth and financial stability.

From this analysis, it is evident that a great deal of importance is placed on understanding the channels through which agricultural commodity prices can be affected by crude oil and macroeconomic factors. In addition, and equally important, we need to establish the extent which to fluctuations in the economy propagates to the agricultural commodity markets. Therefore, it is essential to evaluate the strength of the relationship between agricultural commodity prices and the economic forces driving the price cycles and volatility, particularly since the wakening of the financialization of commodities.

Despite these facts, the empirical literature is very limited with respect to volatility interactions between energy, economic fundamentals and food agricultural commodities Serra [2011]. Instead, the literature has placed a great deal of emphasis on price level transmission mechanisms using supply and demand frameworks, partial/general equilibrium models and vector error correction models, while price volatility interactions between food, energy commodities and fundamentals have received significantly less attention [Serra and Zilberman, 2013]. Consequently, the aim of this study is to contribute to the literature by using a consistent dynamic conditional correlation (cDCC) model by Aielli [2013] in order to measure the degree of co-movement between world oil price returns, the U.S. exchange rate, short-term interest rates and a measurement of or global economic activity with three world traded agricultural commodities used in biofuels production, namely maize, soybean and sugar. Additionally, and in line with Turhan et al. [2014], I will evaluate the stability of the dynamic correlations during the sample period by endogenously detecting any significant shifts using a penalized contrast methodology by Lavielle [2005]. In that sense, the contribution of this research to the current body of literature is to offer an empirical understanding of the volatility spillover over from energy markets, fundamentals to agricultural food markets. Additionally, and where the links exists, I aim to determine if there has been changes in these relationships during the period analyzed.

3.2 Literature Review

In the recent past, researchers have paid close attention to studying the volatility in commodity markets during commodity price boom. For example, Sumner

[2009] points out that the percentage price increase in agricultural commodity markets for this period was the largest in the 140-year history for which U.S. data is available. Similarly, Trujillo-Barrera et al. [2012] showed that historical maize volatility of daily percentage price changes were below 25% before 2006 and since then have increased to over 40% up to 2011. As a result, the literature has resumed its interest in the causal links between agricultural commodity and energy markets and economic fundamentals.

The effects of commodity price volatility can have severe repercussions throughout the economy. For instance, increasing agricultural commodity price volatility is translated into higher costs for managing risks in the form of increasing crop insurance premiums, which in turn translates into higher option premiums and hedging costs for farmers [Wu et al., 2011]. Additionally, as a consequence of the financialization of commodity markets, volatility spillovers from oil prices to agricultural commodity prices can in turn diminish diversification efforts in the financial markets when agricultural and energy prices present any degree of price co-movement [Gardebroek and Hernandez, 2013]. From a macroeconomic point of view, Byrne et al. [2013] explains that the design and effectiveness of stabilization policies are affected by both the volatility and persistence of commodity prices. Moreover, as a consequence of the recent increase in biofuel production, the increased price volatility in agricultural commodities used in biofuels production (e.g. maize, soybeans and sugar) can be transmitted to other agricultural markets. That is, as demand increases for biofuels (as a consequence of the mandates) and assuming that agricultural land is constrained, food production decreases and so increase food prices [Zilberman et al., 2013]. Ultimately, all these effects are reflected in a decrease of welfare in the general population, particularly in the poorest countries, where a higher proportion of income is devoted to food consumption. Therefore, when examining the transmission mechanism in relation to energy volatility between economic fundamentals and food price volatility, it is vital to determine the severity of negative impacts on welfare, for both investment and risk management as well as the impact on economic growth and financial stability.

Despite these facts, the empirical literature is limited with respect to volatility interactions between energy, economic fundamentals and food agricultural commodities [Serra, 2011]. Instead, the literature has placed a great deal of emphasis on price level transmission mechanisms using supply and demand frameworks, partial/general equilibrium models and vector error correction models, while price volatility interactions between food, energy commodities and fundamentals have received significantly less attention [Serra and Zilberman, 2013]. Additionally, and in line with Turhan et al. [2014], we will evaluate the stability of the dynamic correlations during the sample period by endogenously detecting any significant shifts using a penalized contrast methodology by Lavielle [2005].

Economic theory using the standard demand and supply approach has developed several frameworks to explain commodity price dynamics. The main theories used to explain commodity price behavoir are: the storage model, the scarcity rent model, the cobweb model and the overshooting model. The "storage model" was firstly presented by Gustafson [1958], then expanded by Williams and Wright [1991] and Deaton and Laroque [1992], essentially it explains how speculators will engage in commodity trading based on their expectations of future price changes. In summary, the storage model predicts that when current prices are below the traders' future expectations, speculators will store the commodities in order to take advantage of higher future prices. Conversely, when there are no arbitrage incentives to store commodities, price dynamics adjust to demand and supply shocks. Evidently, the storage model theory best explains commodities that are easily storable and whose productions are subject to unpredictable supply shocks.

On the other hand, the "scarcity rent model" has been applied primarily to metal commodities prices and can be traced back to Hotelling [1931]. Since metals pricing concerns the rate of extraction rather than the level of storage, this theory proposes that owners will charge a higher prices (i.e. scarcity rent) for resources that are non-renewable. The theory concludes that price fluctuations will correspond to interest rate changes. However, Hotelling's theory has been widely criticized primarily due to the assumption of finite resource availability, which has been severily undermined by continuous new discoveries and technological changes. The "cobweb model" first introduced by Ezekiel [1938] has been used to explain prices of livestock products and considers price fluctuations to be endogenous, as opposed to exogenous as in the storage model. In both the storage and cobweb theories model how agents form their expectations is important. However, while the storage model considers agents' rational expectations, the cobweb model assumes that producers have naive expectations. Nevertheless, the cobweb model is currently used to determine livestock price dynamics given its ability to generate oscillatory prices which are present in this market, but less so in agricultural commodities.

Finally, there is the "overshooting model" proposed by Frankel [1986, 2008] which emphasizes the importance of macroeconomic factors in explaining commodity price dynamics. In this model, an expansionary monetary policy causes investors to revise upward their future inflationary expectations, which in turn triggers their appetite for investments away from liquid assets towards other investments including commodities. Consequently, commodity prices suffer from upward pressures in their long-run equilibrium and increases proportionally more than the money supply and the general price level in the short-run. This is the so called "overshooting" and this trend will persist as long as commodities are "overvalued" by the market relative to all other goods Stigler [2011].

Nevertheless, the empirical literature is very scarse regarding studies interested on the volatility transmission between energy and agricultural markets. Serra and Zilberman [2013] noted that while the literature has paid much attention to the analysis of price-levels between energy and food commodity prices, there has been a limited number of studies interested in modeling price volatility, volatility interactions and spillovers among these variables. Moreover, it has only been in the past few years that a number of empirical studies have evaluated the magnitude and source of interrelations between energy and agricultural commodity price volatility.

As a result of the commodity price shock of 2006-08, the first studies that focused on volatility transmission between energy and agricultural commodity prices were primarily concerned with the links arising from biofuel production. Zhang et al. [2009] examined the impact of rising ethanol demand on food commodity prices in the U.S. market. For this, Zhang et al. considered a weekly wholesale price series for U.S. ethanol, corn, soybean, gasoline, and oil from 1989 to 2007 using Engle and Kroner [1995] parameterization of the multivariate ARCH process (BEKK-MGARCH). The authors are unable to establish links between volatility in energy and price volatilities in both corn and soybean markets. On the other hand, Serra [2011] uses a semiparametric conditional covariance model as proposed by Long et al. [2011]. Serra [2011] aim is to asses the volatility spillovers from the Brazilian energy to the food market by conducting a pair-wise anlaysis of the price links between crude oil, ethanol and sugar prices. For this study, Serra used monthly price data from mid 2000 to mid 2009. The authors conclude that there is no reason to believe that volatility in the ethanol market does not influence the volatility in sugar prices; however, Serra did not study the transmission links between crude oil and sugar price volatility. On the other hand, Wu et al. [2011] investigated the oil price volatility spillover to corn price volatility in the U.S. from 1992 to 2009 using an asymmetric MGARCH model. Wu et al. show that, during this period for the U.S., there is a positive spillover between crude oil prices to corn prices.

Other authors have explored the volatility spillovers in the futures markets between energy and agricultural markets. For example, Du et al. [2011] used weekly data from 1998 to 2009 to study the spillover from crude oil to agricultural commodity prices using stochastic volatility models. They find no evidence of volatility spillover from oil to agricultural commodity futures prices for the first part of their sample, but after 2006 the results indicate a strong volatility spillover effect from oil crude oil to agricultural commodity futures markets. Likewise, Trujillo-Barrera et al. [2012] analyzed the volatility spillovers from crude oil to corn prices in the U.S. futures market from 2006 to 2011. Here, the authors estimated that approximately 10% of corn price variability can be attributed to volatility in the crude oil market and reached about 45% during the financial turmoil of 2008. More recently, Gardebroek and Hernandez [2013] examined the level of interdependence among oil and corn price volatility in the U.S. between 1997 and 2011 by estimating a BEKK-MGARCH model as well as a dynamic conditional correlation (DCC) model by Engle [2002]. The authors are unable to conclude any cross-volatility effects from oil to corn markets. These results are particularly relevant since they imply that (at least in the U.S.) there is no evidence that volatility form energy markets spurs towards corn prices. One possible reason why this might be is that the market short-run shocks affecting crude oil prices are not teh same or synced with those experienced in the agricultural commodity markets.

More recently, the empirical literature has placed more emphasis on studying the spillover effects from crude oil and commodity return prices. Busse and Ihle [2009] applied a DCC-MGARCH model to daily price returns of crude from 1999 to 2009, and related agricultural commodity prices (e.g. soybeans, rapeseed) and found an increasing correlation between crude oil price returns and agricultural commodity series. Onour and Sergi [2011] studied the volatility spillover across crude oil and wheat and corn monthly return prices from 1992 to 2011 by using a BEKK-MGARCH model. Onour and Sergi find no evidence of crude oil volatility transmission to global corn and wheat markets; moreover, the authors only found evidence from corn to wheat return prices. Similarly, Musunuru [2014] using the same methodology corroborates Onour and Sergi results on the linkages between corn and wheat return prices. On the other hand, Nazlioglu et al. [2013] investigates the volatility transmission using daily observations from January 1986 to March 2011 using univariate GARCH models and subsequently by applying the causality in variance test by Hafner and Herwartz [2006] between oil and world wheat, corn, soybeans, and sugar return prices. This test is derived from the initial work of Cheung and Ng [1996] and Hong [2001] who developed a causality-in-variance test based on cross-correlation functions (CCF) of standardized residuals which are obtained from univariate general autoregressive conditional heteroscedasticity (GARCH) estimations. However, according to Hafner and Herwartz [2006] the CCF based Portmanteau test suffers from significant oversizing in small and medium samples when the volatility processes are leptokurtic. Moreover, CCF test is sensitive to the orders of leads and lags which hinders the robustness of the findings. On the other hand, Hafner and Herwartz's volatility spillover test is based on the Lagrange multiplier (LM) principle which overcomes the shortcomings of Cheung and Ng [1996] and Hong [2001] method. In addition, Monte Carlo experiments by Hafner and Herwartz [2006] show that the LM approach is significantly more robust against leptokurtic innovations in small samples and it increases with the sample size.Nazlioglu et al. find no evidence of volatility transmission between oil and world agricultural commodity markets before the 2006-08 period, but find strong spillover evidence from oil to mosts agricultural markets studied. de Nicola et al. [2014] examine the co-movement among the nominal price return of 11 major energy, agricultural, and food commodities using monthly data between 1970 and 2013 using a DCC-MGARCH model and find that price return of energy and agricultural commodities present high level of correlation during this period and more so in the recent past. Likewise, Mensi et al. [2014] using daily spot price return of a number of energy and cereal markets from January 2000 to January 2013 apply a BEKK-MGARCH and DCC-MGARCH models in order to examine the dynamic returns and volatility spillovers across these markets. Mensi et al. provide substantial evidence of significant linkages between daily spot energy and cereal price returns during this period.

As outlined earlier, most studies have focused on the volatility transmission between energy and agricultural markets, but hardly any has attempted to incorporate macroeconomic effects into the analysis. Moreover, the majority of these studies have only been interested in the spillover effects between energy markets and the exchange rate and only recently stock market returns. An early study by Narayan et al. [2008] apply a exponential GARCH (EGARCH) model in order to estimate the impact of crude oil price returns on the nominal Fijian and U.S. dollar exchange rate using daily data from 2000-06. In this study the authors establish a positive relationship between crude oil price return and the Fijj-U.S. dollar exchange rate. Turhan et al. [2014] applied a cDCC model to evaluate the dynamic correlations between oil and the exchange rate using the U.S. dollar and G20 countries. Turhan et al. conclude that there exists a strong negative correlation between crude oil price returns and the exchange rate of G20 members as well as finding that these correlations have suffered from significant structural changes, particularly since the 2006-08 commodity price shock. On the other hand, Manera et al. [2013] are interested in investigating whether macroeconomic factors are able to explain returns of energy and five world agricultural commodities (i.e. corn, oats, soybean oil, soybeans and wheat) using weekly data over the period 1986 to 2010 with pair-wise DCC-MGARCH models. The authors find that financial speculation is not correlated with returns for these energy and agricultural series. Nevertheless, Manera et al. present significant and positive conditional correlations among energy and agricultural commodities, which suffered dramatic strengthening during the 2006-08 period. Finally, Serra and Gil [2013] studied the volatility spillovers from energy prices, global economic conditions (3-Month U.S. Treasury bill) and U.S. corn price volatility from January 1990 to December 2010 using a two-stage process. In the first stage, Serra and Gil use a conventional parametric two-dimensional GARCH and then apply the Long et al. [2011] nonparametric correction of the parametric conditional covariance estimators. Serra and Gil [2013] find that interest rate variability is associated with more volatile corn prices. As a consequence, the authors recommend expanding the analyses of volatility spillovers among energy and agricultural markets by considering a wider range of explanatory variables

[Serra and Gil, 2013].

The contribution to the current body of literature is twofold. First, this study expands the analysis of volatility interdependence between world energy and food agricultural markets by considering global macroeconomic factors and crude oil prices in a VAR-cDCC-MGARCH model.Secondly, we analyze the volatility interactions using a comprehensive sample period of 30 years that allows us to examine whether there have been changes in the dregree of the dependency among these variables as well as significant shifts in the dynamics of volatility during the same period. Additionally, we show that by correctly specifying the univariate GARCH we overcome one of the shortcomings from estimating a large number of coefficients and problems that arise from it while maximizing the likelihood function. Finally, we are interested in detecting significant changes in the dynamic correlations between these variables and in particular during and after the 2006-08 commodity price turmoil. Therefore, we analyze the degree of volatility interdependence across time between these markets by first estimating a Consistent Dynamic Conditional Correlation (cDCC) model by Aielli [2013] using a Student's t density for the estimation of the cDCC model. This methodology is pivotal given the contemporary discussions in the literature on the links between energy and agricultural commodity markets during and after the years leading to the recent commodity price shock. The cDCC model is useful since it allows us to estimate the correlation matrix as time dependent as supposed to the CCC model where the correlation matrix is assumed constant over time[1]. Moreover, the cDCC models allows to analyze the time-varying conditional correlations between these commodity price returns with crude oil and macroeconomic variables. Subsequently, we endogenously estimate any structural changes in the

[1]A mode detail explanation on the different characteristics of these models and their justifications is exposed in the next section.

estimated dynamic correlations using a penalized contrast methodology proposed by Lavielle [2005] and recently applied by Turhan et al. [2014].

3.3 Methodology

3.3.1 The General Multivariate GARCH (MGARCH) Model

Let us consider a column vector of excess returns $\{r_t\}$ of dimensions $N \times 1$ for $t = 1, \dots, T$ such that $E(r_t|\mathcal{F}_{t-1}) = 0$ and $Var(r_t|\mathcal{F}_{t-1}) = H_t$. We denote $\mathcal{F}_{t-1}$ as the information set generated by the past observations of the series $\{r_t\}$ up to time $t-1$ [Mikosch et al., 2009]. Multivariate GARCH models are assumed to be conditionally heteroskedastic given the information set $\mathcal{F}_{t-1}$ and can be represented as follows:

$$r_t = \mu_t(\theta) + \varepsilon_t \tag{3.1}$$

where θ is a finite vector of parameters, $\mu_t(\theta)$ is the vector of conditional expectations of r_t is conditionally heteroskedastic such that:

$$r_t - \mu_t(\theta) = \varepsilon_t = H_t^{1/2}(\theta)\eta_t \tag{3.2}$$

where $H_t^{1/2}(\theta)$ is any $N \times N$ positive define matrix of conditional variance of r_t such that $H_t^{1/2}$ is any square matrix such that $H_t = H_t^{1/2}(H_t^{1/2})'$ and where η_t is an unobservable random $N \times 1$ *iid* vector error process with zero mean $(E(\eta_t = 0))$ and identity matrix $(E(\eta_t\eta_t') = Var(\eta_t) = I_N)$. Thus, $\eta_t \sim N(0, I_N)$, where I_N is the identity matrix of order N. Therefore, the conditional variance matrix of r_t can be calculated as follows:

$$\begin{aligned} Var(r_t|\mathcal{F}_{t-1}) = Var_{t-1}(y_t) &= Var_{t-1}(\varepsilon_t) \\ &= H_t^{1/2} Var_{t-1}(\eta_t)(H_t^{1/2})' \\ &= H_t \end{aligned}$$

Consequently, $H_t^{1/2}$ is any symmetric, positive definite matrix of dimensions $N \times N$ such that H_t is the conditional variance matrix of r_t. $H_t^{1/2}$ can also be triangular, with positive diagonal elements (e.g. it can be obtained by the Cholesky factorization of H_t). It is the case that H_t and μ_t depend on the unknown parameter θ. In some cases μ_t functionally depends on H_t, in which case θ has to be jointly estimated (GARCH-in-mean models); however in most cases it is possible to split θ into two disjointed parts, one corresponding for μ_t and another for H_t [Laurent et al., 2006].

3.3.2 Constant Conditional Correlation (CCC) Model

Constant Conditional Correlation GARCH (CCC-GARCH) models were was first proposed by Bollerslev [1990]. CCC-GARCH models are multivariate models were conditional variances and covariances are time-varying and proportional to the product of the corresponding conditional standard deviations, but with constant conditional correlations. In other words, correlation models decompose the conditional covariance matrix into conditional standard deviations and correlations [Silvennoinen and Teräsvirta, 2008]. According to Laurent et al. [2006], this parameterization of the conditional heteroskedasticity significantly simplifies the estimation procedure by reducing the number of unknown parameters.

Let us suppose that an MGARCH process takes the form described in Equation 3.2. Let $h_{ij,t}$ denote the ij^{th} element in the conditional variance-covariance matrix (H_t), and r_{it} and ε_{it} the i^{th} element in r_t and ε_t respectively as previously defined[2]. In CCC-GARCH models we specify the conditional variances $h_{ij,t}$ for $i = 1, 2, \ldots, N$ and the conditional correlations $\rho_{ij,t}$ as proportional to the square root of the product of the corresponding two conditional variances,

$$\rho_{ij,t} = \frac{h_{ij,t}}{\sqrt{h_{ii,t}h_{jj,t}}}, \tag{3.3}$$

$$\forall\ i = 1, 2, \ldots, N \text{ and } j = i + 1, \ldots, N,$$

where -1 $\leq$ $\rho_{ij,t}$ $\leq$ 1 for all t. Consequently, the conditional correlation is also the conditional covariance between the standardized disturbances Engle [2002]. Naturally, one would expect the conditional correlations ($\rho_{ij,t}$) will be time varying as H_t varies across time. However, CCC-GARCH models (as the name suggests) the conditional correlation matrix is constant over time. Thus, the full conditional covariance matrix of the return, H_t, can be rewritten as follows

$$E_{t-1}(r_t r_t') \equiv H_t = D_t R D_t, \tag{3.4}$$

where $D_t \equiv diag(h_{1t}^{1/2}, h_{2t}^{1/2}, \ldots, h_{Nt}^{1/2})$ is a diagonal matrix $N \times N$ with h_{it} as the i^{th} diagonal element, and $R \equiv [\rho_{ij}]$ is the matrix containing the constant conditional correlations ρ_{ij} of order N (implying $\rho_{ii} = 1\ \forall\ i$ and j). Therefore, the off-diagonal elements of the conditional covariance matrix are defined as:

$$H_t = h_{it}^{1/2} h_{jt}^{1/2} \rho ij,\ \forall\ i \neq j \tag{3.5}$$

[2] In practice, ε_{it} is often assumed to follow the standard normal or a standardized Student-t distribution or a generalized error distribution [Tsay, 2014].

As before, H_t is a positive definite if and only if each of the N conditional variances are well defined (i.e. $h_{it}^2 > 0$) for all i and R is also positive definite [Bauwens et al., 2012]. Evidently, the challenge of this type of model is to ensure that R is a positive definite that does not depend in a large number of parameters which in turn is not estimable. In order to address this issue, Bollerslev [1990] makes the crucial assumption that we have time-invariant conditional correlations and for this reason all CCC-GARCH models assume a constant correlation matrix.

The specification of H_t is divided into a specification for each conditional variance and one for the conditional correlation matrix. Each conditional variance is specified as a function of its own lags and the i^{th} element of r_t. Thus, a CCC-GARCH (p, q) process is defined as the sequence of iid variables (η_t) with distribution η. Then the process r_t is called a CCC-GARCH (p, q) process as long as it satisfies the following conditions:

$$\begin{cases} \varepsilon_t = H_t^{1/2}\eta \\ H_t = D_t R D_t \\ h_t = \omega_i + \sum\limits_{j=1}^{q} \mathbf{A}_j r_{t-j}^{(2)} + \sum\limits_{j=1}^{p} \mathbf{B}_j h_{t-j},\ i = 1, 2, \ldots, N \end{cases} \tag{3.6}$$

where R is the correlation matrix, ω is $N \times 1$ vector with positive coefficients, and the $\mathbf{A}_j$ and $\mathbf{B}_j$ are diagonal $N \times N$ matrices with nonnegative coefficients; $r_{t-j}^{(2)} \equiv r_t \odot r_t$, where $\odot$ denotes the Hadamard (i.e. element-wise) product of two conformable matrices. The covariance matrix H_t is positive definite as long as R is positive definite and the elements of ω and the diagonal of $\mathbf{A}_j$ and $\mathbf{B}_j$ are positive [Francq and Zakoian, 2010].

One of the main advantages of the CCC-GARCH model is its computational attractiveness. The the log-likelihood of the decomposition presented in Equation 3.4 takes the following form:

$$\sum_{t=1}^{T} l_t(\theta) = c - \left(\frac{1}{2}\right)\sum_{t=1}^{T}\sum_{i=1}^{N} ln(h_{it}) - \left(\frac{1}{2}\right)\sum_{t=1}^{T} log|P| - \left(\frac{1}{2}\right)\sum_{t=1}^{T}\left(r_t' D^{-1} P^{-1} D^{-1} r_t\right) \tag{3.7}$$

From Equation 3.7, the conditional correlation has to be inverted only once per iteration and the number of parameters to be estimated is reduced to $N(N-1)/2$. The covariance stationarity is assured as long as the roots of the $\det(\mathbf{I} - \sum_{j=1}^{q} \mathbf{A}_j \lambda_j - \sum_{j=1}^{p} \mathbf{B}_j \lambda_j) = 0$ lays outside the unit circle [Silvennoinen and Teräsvirta, 2008].

A drawback arising from the CCC-GARCH model is the unrealistic assumption of the time invariant nature of the conditional correlations. In order to address this limitation, both Tse and Tsui [2002] and Engle [2002] propose a generalization of the CCC-GARCH model by allowing the conditional correlation matrix to be time variant.

3.3.3 Dynamic Conditional Correlation (DCC) and Aielli [2013] cDCC models

Dynamic conditional correlations GARCH (DCC-GARCH) models are a generalization of the CCC models, which were first proposed by Tse and Tsui [2002] and Engle [2002]. DCC-GARCH models relax the arbitrary assumption of constant conditional correlations of CCC-GARCH models and introduce a dynamic for these conditional correlations. Thus, in the DCC-GARCH models, the matrix R is replaced by a matrix R_t, which is quantified with respect to past variables. Similarly, H_t is the conditional covariance matrix of the vector of the standardized returns that is modeled as a function of the past standardized returns. Here, I only focus on the Engle [2002] DCC-GARCH model where the the conditional covariance matrix $H_t \equiv E_{t-1}[r_t r_t']$ is given as:

$$H_t = D_t \; R_t \; D_t, \tag{3.8}$$

where $R_t \equiv \rho_{ij,t}$ is a $N \times N$ symmetric and positive definite matrix parameter of the asset conditional correlation matrix, R_t is a correlation matrix as long as R_{t-1} is also a correlation matrix where $R_t = \rho_{ii,t} = 1 \; \forall \; i$; $D_t \equiv diag(h_{11,t}^{1/2}, h_{22,t}^{1/2}, \ldots, h_{NNt}^{1/2})$ is the diagonal matrix of conditional variances as diagonal elements of D_t as in Equation 3.4.

In the DCC-GARCH model, the diagonal elements of D_t are modeled as univariate GARCH models. The conditional correlation matrix is then modeled as a function of the past standardized returns, such that

$$R_t = Q_t^* \; Q_t \; Q_t^*, \tag{3.9}$$

where

$$Q_t = (1 - \alpha - \beta)S + \alpha(\eta_{t-1}\eta_{t-1}') + \beta Q_{t-1}$$

where, $Q_t^* \equiv q_{ij,t}$, $Q_t^* \equiv diag(q_{11,t}^{-1/2}, q_{22,t}^{-1/2}, \ldots, q_{NNt}^{-1/2})$, $S = T^{-1}/\sum \eta_t \eta_t'$ is an $N \times N$ unit-diagonal unconditional correlation matrix of the standardized errors and $\eta_t = \varepsilon_t/\sqrt{h_{i,t}}$ are the standardized residuals from the GARCH model. Finally, α is positive and β is a non-negative scalar parameters such that $\alpha + \beta < 1$. Consequently, H_t is a positive definite as long as R_t and S are also positive definite and $\alpha \geq 0$, $\beta \geq 0$ and $\alpha + \beta < 1$ [Bauwens et al., 2012]. In this specification we can test the assumption of the constant conditional correlation covariance matrix by performing a Wald test on the restriction $\alpha = \beta = 0$ [Francq and Zakoian, 2010].

Engle's DCC-GARCH model extends the CCC-GARCH model at the expense of extra parameters to estimate [Engle, 2002]. For each correlation equation, the number of estimated parameters is $N(N-1)/2+2$. This is a strength, but also a weakness when considering large N since the correlation processes are restricted to have the same dynamic structure. Thus, it has been argued that in large systems DCC-GARCH estimators can be inconsistent [Aielli, 2013] .

Moreover, Aielli [2013] has shown that the estimation of D by Maximum Likelihood (ML) of R, which is given by

$$\widehat{R} = \frac{1}{T}\sum_{t=1}^{T} \widetilde{r}_t \widetilde{r}_t{}', \tag{3.10}$$

where $\widetilde{r}_t = R_t^{-1} r_t$, is inconsistent for large N since $E(\widetilde{r}_t \widetilde{r}_t{}') = E(E(\widetilde{r}_t \widetilde{r}_t{}' | \mathcal{F}_{t-1})) = E(r_t) \neq E(Q_t)$ [Bauwens et al., 2012]. Thus, Aielli [2013] proposes a different specification for Q_t that in this case is consistent and thus the name (cDCC, consistent DCC). Thus, the DCC model can be substantially improved by reformulating the correlation driving process as

$$Q_t = (1-\alpha-\beta)S + \alpha\left\{Q_t^* \tilde{r}_{t-1} \tilde{r}_{t-1}' Q_t^*\right\} + \beta Q_{t-1}, \tag{3.11}$$

where $Q_t^* \equiv diag(q_{11,t}^{1/2}, \ldots, q_{NN,t}^{1/2}) = (I_N \odot Q_t)^{1/2}$, thus Q is the unconditional variance covariance matrix of $Q_t^* \tilde{r}_t$. For example, in the bivariate case the correlation is defined as follows:

$$\rho_{ij,t} = \frac{\omega_{ij} + \alpha r_{i,t-1} r_{j,t-1} + \beta \rho_{ij,t-1}}{\sqrt{\left\{\omega_i + \alpha r_{i,t-1}^2 + \beta \rho_{ii,t-1}\right\}\left\{\omega_{jj} + \alpha r_{j,t-1}^2 + \beta \rho_{jj,t-1}\right\}}}, \tag{3.12}$$

where $\omega_{ij,t} \equiv (1-\alpha-\beta)s_{ij}/\sqrt{q_{ii,t}q_{jj,t}}$. From Equation 3.12, is evident that "…the relevant innovations and past correlations are combined into a correlation-like ratio." The parameters α and β are the dynamic parameters of the correlation GARCH and the denominator of the time-varying parameters $\omega_{ij,t}$, $\omega_{ii,t}$ and $\omega_{jj,t}$ can be interpreted as ad hoc correction required for purposes of tractability [Aielli, 2013].

Multivariate Conditional *t*-Distribution

The literature highlights that empirical distributions of returns residuals suffer from kurtosis (i.e. fat-tailed) more than predicted by the Gaussian distribution [Blattberg and Gonedes, 1974, Franses and van Dijk, 2000]. Therefore, under these conditions multivariate parametric models with a t-student distribution of the error term are useful in capturing the characteristics of the time series data [Ait-Sahalia and Hansen, 2009]. Following Bollerslev [1987], given that the unconditional excess kurtosis of ε_t is an increasing function of the kurtosis of η_t, we can then assume that η_t follows a *Student's-t*[3] distribution with ν degrees of freedom, that is,

$$\begin{aligned} f(\eta_t) =& \Gamma\left(\frac{n+k}{2}\right)\Gamma\left(\frac{\nu}{2}\right)^{-1}\left((\nu-2)h_{t|t-1}\right)^{-1/2} \\ & \times\left(1+\varepsilon_t^2 h_{t|t-1}^{-1}(v-2)^{-1}\right) \end{aligned}$$

where $\Gamma(\cdot)$ is the Gamma function. It is known that the *t-distribution* is sym-

[3] It follows a leptokurtic distribution as supposed to a standard normal distribution assumed before.

metric around 0 and that it approaches to the normal distribution for $1/\nu \to 0$ but for $1/\nu > 0$ the t-distribution has "fatter tails" than the corresponding normal distribution. A further characteristic of the t-distribution is that only moments up to order ν exists (otherwise, these are undefined); thus, for $\nu > 4$ the variance and the fourth moment are well defined. Furthermore, one does not need to define the number of degrees of freedom of the Student-t distribution a priori. Instead, ν can be estimated as an additional parameter along the other parameters in the model [Tsay, 2014].

3.3.4 Endogenous detection of the shifts in dynamic correlations

The methodology developed by Lavielle [2005], which is based on a penalized contrast is applied in order to determine any shifts in both mean and variance (and the respective locations) of the dynamic correlations along the entire sample period. Here we consider a sequence of random variables $Y_1, \ldots, Y_n$ that take values in $\mathbb{R}^p$. Lets denote the parameter $\theta \in \Theta$ some characteristics of Y_i that changes abruptly at some unknown interval and which remains constant between these two changes. Now, we define K to be some integer and let $\tau = (\tau_1, \tau_2, \ldots, \tau_{K-1})$ be a sequence of integers satisfying $0 < \tau_1 < \tau_2 < \cdots < \tau_{K-1} < n$. Thus, for any $1 \leqslant k \leqslant K$ let $U(Y_{\tau_{k-1}+1}, \ldots, Y_{\tau_k}; \theta)$ be a contrast function used for determining the unknown true value of the parameter of the segment k. Particularly, the minimum contrast estimate $\hat{\theta}(Y_{\tau_{k-1}+1}, \ldots, Y_{\tau_k})$ calculated on segment k of τ can be obtained as a solution of the following minimization problem:

$$U(Y_{\tau_{k-1}+1}, \ldots, Y_{\tau_k}; \hat{\theta}(Y_{\tau_{k-1}+1}, \ldots, Y_{\tau_k})) \leqslant U(Y_{\tau_{k-1}+1}, \ldots, Y_{\tau_k}; \theta), \; \forall \; \theta \in \Theta$$

For any $1 \leqslant k \leqslant K$, lets define G as,

$$G(Y_{\tau_{k-1}+1}, \ldots, Y_{\tau_k}) = U(Y_{\tau_{k-1}+1}, \ldots, Y_{\tau_k}; \hat{\theta}(Y_{\tau_{k-1}+1}, \ldots, Y_{\tau_k})) \tag{3.13}$$

Then, define the contrast function $J(\tau, \mathbf{y})$ to be

$$J(\tau, \mathbf{y}) = \frac{1}{n} \sum_{k=1}^{K} G(Y_{\tau_{k-1}+1}, \ldots, Y_{\tau_k}) \tag{3.14}$$

where $\tau_0 = 0$ and $\tau_k = n$.

When the true number $K^\star$ of segments is known, the sequence $\hat{\tau_n}$ of change-point instants that minimizes the contrast function defined above follows the requirement that for any $1 \leqslant k \leqslant K^\star - 1$,

$$P\left(|\tau_{n_k} - \tau_k^\star| > \delta\right) \to 0$$
$$\text{as long as } \delta \to \infty \text{ and } n \to \infty$$

In particular, this result holds for weakly and strongly dependent processes. For example, lets consider the model with the following characteristics:

$$Y_i - \mu_i + \sigma_i \varepsilon_i,\ 1 \leqslant i \leqslant n$$

where ε_i is a sequence of zero-mean random variables with unit variance. In case of changes in the mean, it is assumed that μ_i is a piecewise constant sequence and σ_i is a constant sequence. Therefore, there occur some instants $\tau_1^\star < \tau_2^\star < \cdots < \tau_{K^\star-1}^\star$ such that, for any $1 \leqslant k \leqslant K$, $\mu_{\tau_{k-1}^\star+1} = \mu_{\tau_{k-1}^\star+2} = \cdots = \mu_{\tau^\star}$. A key advantage of this methodology is that Gaussian log-likelihood can be used to define the contrast function, even if ε_i is not a Gaussian sequence. That is, let

$$U(Y_{\tau_{k-1}+1}, \dots, Y_{\tau_k}; \mu) = \sum_{i=\tau_{k-1}+1}^{\tau_k} (Y_i - \mu)^2 \tag{3.15}$$

Then,

$$G(Y_{\tau_{k-1}+1}, \dots, Y_{\tau_k}) = \sum_{i=\tau_{k-1}+1}^{\tau_k} \left(Y_i - \bar{Y}_{\tau_{k-1}+1:\tau_k}\right)^2 \tag{3.16}$$

where $\bar{Y}_{\tau_{k-1}+1:\tau_k}$ is the empirical mean of $(Y_{\tau_{k-1}+1}, \dots, Y_{\tau_k})$. Similarly, if the changes affect both the mean and the variance, a contrast function based on a Gaussian log-likelihood is given by

$$G(Y_{\tau_{k-1}+1}, \dots, Y_{\tau_k}) = (\tau_k - \tau_{k-1})\mathbf{log}\left(\sigma^2_{\tau_{k-1}+1:\tau_k}\right) \tag{3.17}$$

where

$$\sigma^2_{\tau_{k-1}+1:\tau_k} = \frac{1}{(\tau_k - \tau_{k-1})} \sum_{i=\tau_{k-1}+1}^{\tau_k} \left(Y_i - \bar{Y}_{\tau_{k-1}+1:\tau_k}\right)^2 \tag{3.18}$$

On the other hand, when the number of shifts are unknown, these can be estimated by minimizing a penalized version $J(\tau, \mathbf{y})$ described above. That is, for any sequence of change point segments τ, let $pen(\tau)$ be an increasing function of $K(\tau)$. Then , let $\hat{\tau}_n$ be the sequence of change-point instants that minimizes

$$H(\tau) = J(\tau, \mathbf{y}) + \beta \cdot pen(\tau) \tag{3.19}$$

where β is a function of n that approaches to zero as n goes to infinite and the estimated number of segments $K_{\hat{\tau}_n}$ converges in probability to $K^\star$. The adequate penalization parameter β and the function $pen(\tau)$ are chosen according to Lavielle

[2005].

3.4 Data Description

The objective of this analysis is to examine the volatility transmission between a number of macroeconomic variables (i.e. real exchange rate, short-term interest rate and a measurement of or global economic activity), world crude oil prices and three world traded agricultural commodities used in the production of bio-fuels, namely maize, soybean and sugar. The data used in this analysis have a a monthly frequency and the observations span from January 1982 until December 2012 (See Table 3.1). This sample period captures all major macroeconomic as well as commodity cycles over the past three decades as well as important institutional changes affecting both the energy and agricultural markets.

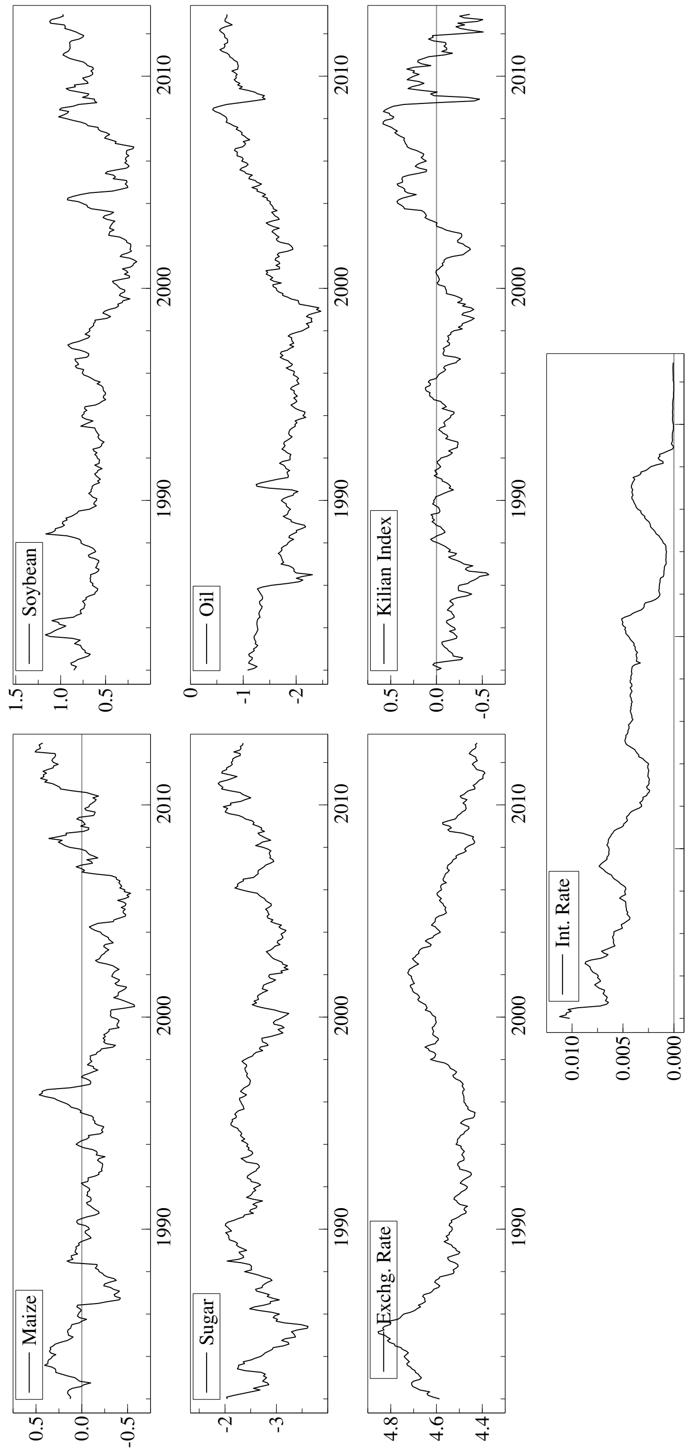
Table 3.1: *Data Definition and Source*

Variable	Frequency	Range	Units	Source	Code
Maize (MZ_t)	Monthly	Jan 1982 Dec 2012	U.S. Dollars per Metric Ton	IFS	PZPIMAIZ
Soybean ($SOYB_t$)	Monthly	Jan 1982 Dec 2012	U.S. Dollars per Metric Ton	IFS	PZPISOYB
Sugar (S_t)	Monthly	Jan 1982 Dec 2012	U.S. Dollars per Metric Ton	IFS	PZPISUG
Crude Oil (O_t)	Monthly	Jan 1982- Dec 2012	U.S. Dollars per Barrel	IFS	PZPIOIL
PPI (P_t)	Monthly	Jan 1982- Dec 2012	Index (1982=100)	FRED	PPIACO
Three-Month T-Bill (I_t)	Monthly	Jan 1982- Dec 2012	Percentage	FRED	TB3MS
Trade Weighted USD Index (XR_t)	Monthly	Jan 1982- Dec 2012	Real Index (1997=100)	FRED	TWEXBMTH
Indx. Global Econ. Activity (Y_t)	Monthly	Jan 1982-	Index	Lutz Kilian	-

The real exchange rate (XR_t) is defined as the weighted average of the foreign exchange values of the U.S. dollar against the currencies of major U.S. trading partners converted to real terms and was obtained from and constructed by the Board of Governors of the Federal Reserve System. For the short-term interest rate (i_t) we have used the three-month Treasury bill secondary market rate as reported by the Federal Bank of St. Louis in the FRED database. Moreover, we have used Kilian's index as a proxy for the real global economic activity as defined in Kilian [2009]. We also included the world price of crude oil (O_t) measured as the trade weighted average price of crude oil in U.S. dollars per barrel, obtained from the IMF International Financial Statistics (IFS). On the other hand, the three agricultural commodities of interest are the price of maize (MZ_t), soybean (SB_t) and sugar (S_t), which were all obtained from the IFS database and are measured in U.S. dollars per metric tonne. All these agricultural price variables are world benchmark price series which are representative of the global market and are determined by the largest exporter of this specific commodity (Table 3.1). All price series have been deflated using the the U.S. Producer Price Index (PPI) for all commodities (not seasonally adjusted) since the variables of interest are widely used as intermediate goods in industrial production. Furthermore, all the analysis is conducted un returns defined as $r_t = log(y_t/y_{t-1})$ where y_t corresponds to the series "y" at month t.

Figure 3-1 and 3-2 show the fluctuations of the series in the past thirty years in real terms. At first sight these series appear to be remarkably similar, particularly the commodity and crude oil price series at the end of the sample. There, is evidence of the increasing mean since 2000 in all series with a significant growth rate during the commodity and energy price boom leading up to 2007/08 and subsequent bust during the financial crisis at the end of 2008 and then the recovery after the instability period. Thus, one can easily corroborate the real price co-movement argued in the previous chapter. Also, it is worth noting the market specific shocks for each of the commodity series that are common across commodity price markets and appear to be short lived, but significant in terms of price volatility.

Figure 3-1: *Logarithm of Prices and Macroeconomic Factors Adjusted for PPI (1982-84=100)*



Figures 3-3 and 3-4 show the return of these series across the entire sample period where the correlation across these commodity price returns are less evident. In particular, this is the case in the middle part of the sample period where the series experience very low levels of volatility. During the 80's, the series experienced high levels of volatility due to the collapse in commodity prices and exogenous shocks (e.g. crude oil). During the 90's all series present a fair level of stability in terms of their volatility levels, but this is short-lived after the end of the millennium when the series begin to experience higher levels of fluctuations primarily up to the 2008 financial crisis also found by Gardebroek and Hernandez [2013] (See Figures 3-3-3-4). Informally, these figures show the remarkable low return correlation between these commodity prices and crude oil and instead shows a strong correlation between these and economic fundamentals as suggested by the findings from Gardebroek and Hernandez [2013] in the sample from 1997 to 2011. Instead, the sources of higher volatility towards the end of the sample are present in the macroeconomic variables, particularly in the short-term interest rate, Kilian index and real exchange rate respectively. Thus, there exists some strong evidence indicating a co-movement in volatility of these series that also coincides with the fluctuations in the macroeconomic fundamentals, particularly in the latter part of the sample.

Figure 3-2: *Logarithm of Prices and Macroeconomic Factors Returns (1982-2012)*

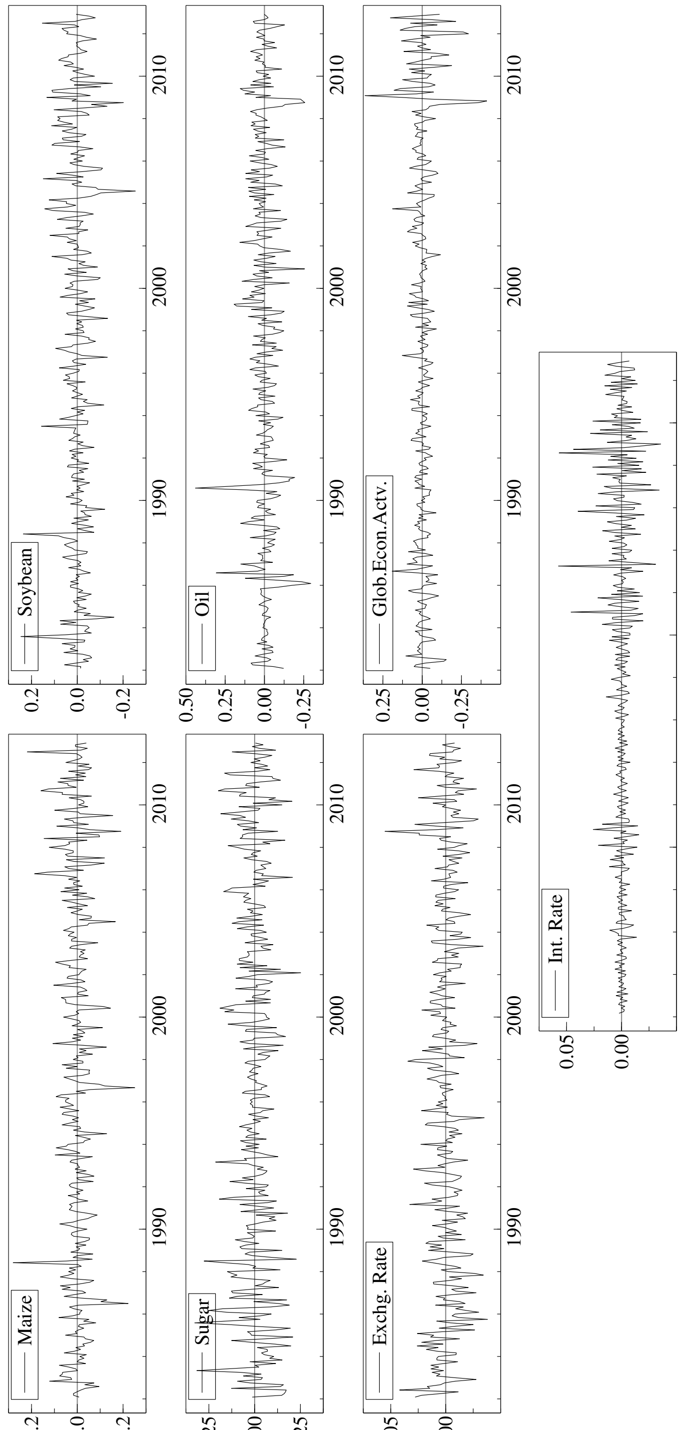
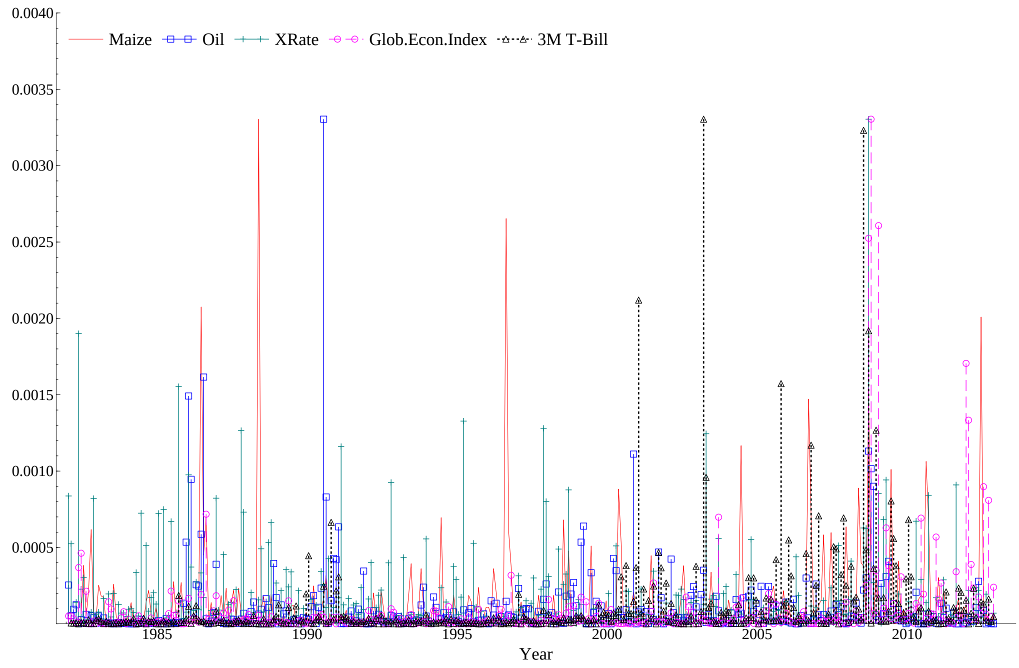
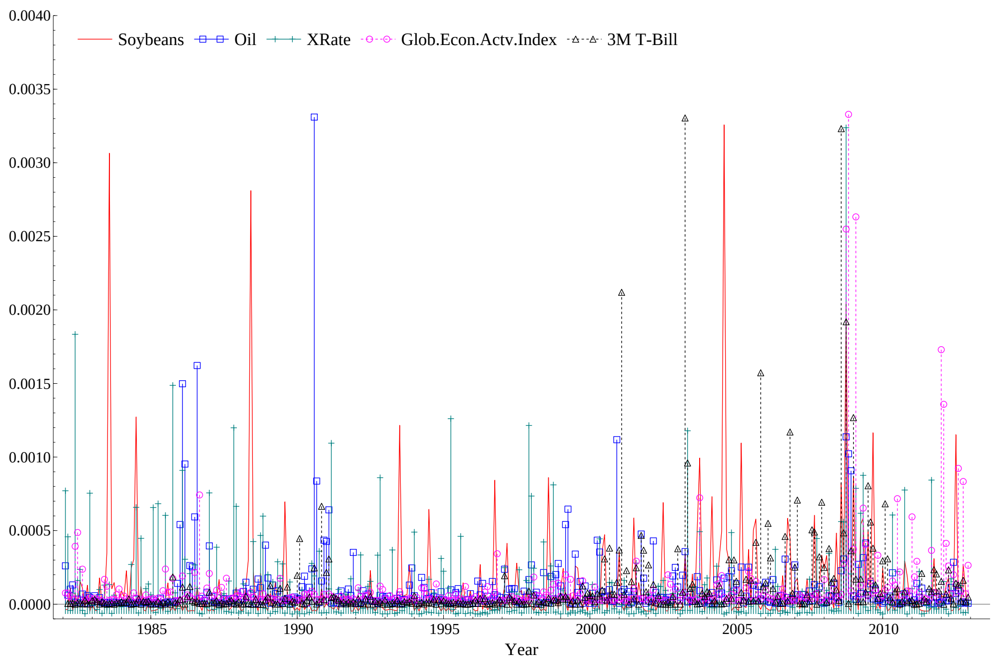


Figure 3-3: *Monthly Price Returns and Macroeconomic Factors (1982:01-2012:12)*

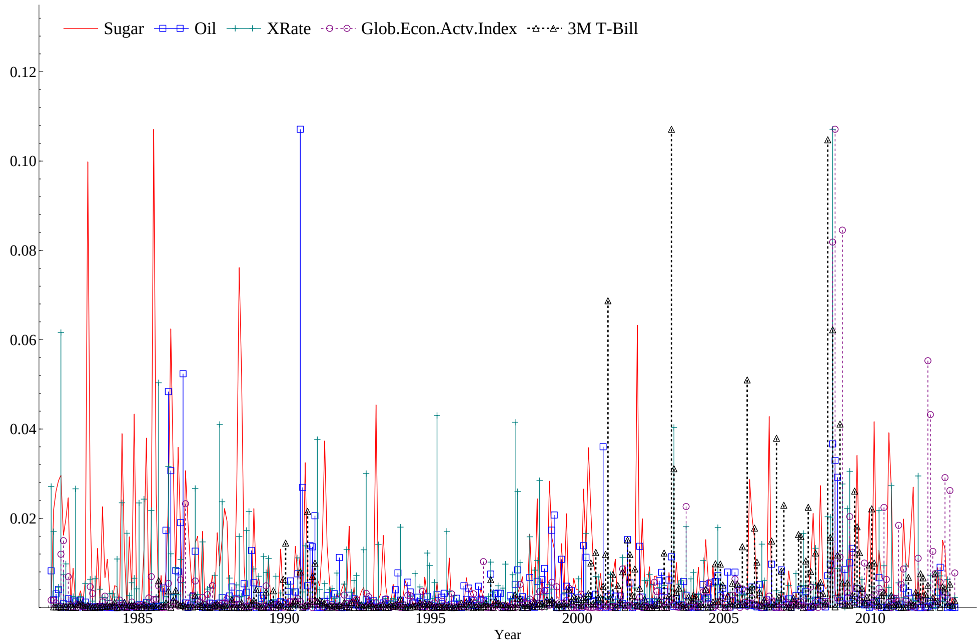


(a) *Maize with Macroeconomic Factors*

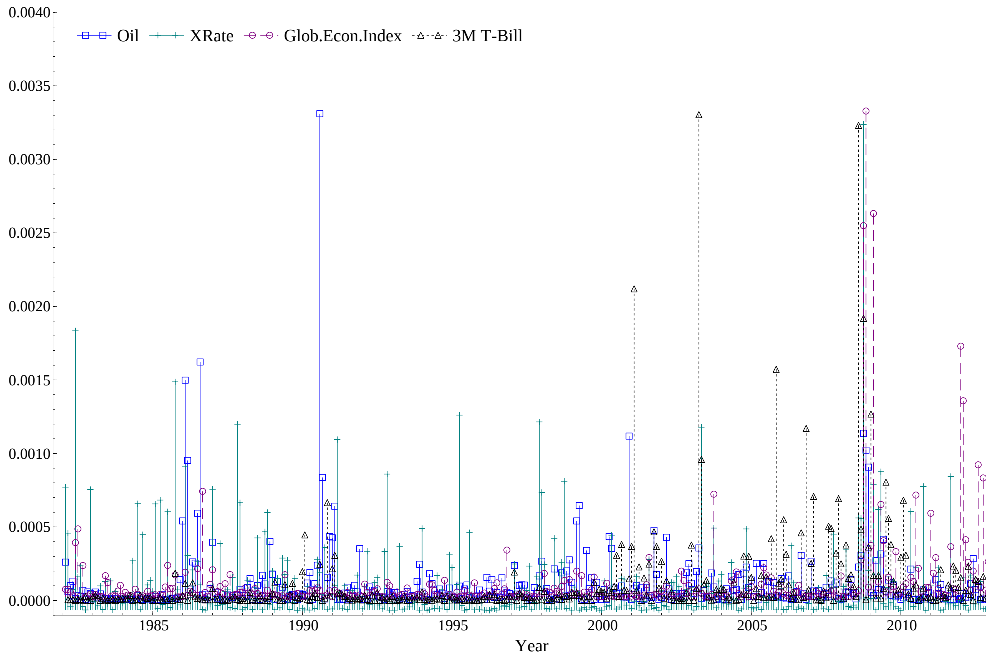


(b) *Soybeans with Macroeconomic Factors*

Figure 3-4: *Monthly Price Returns and Macroeconomic Factors (1982:01-2012:12)*



(a) *Sugar with Macroeconomic Factors*



(b) *Oil with Macroeconomic Factors*

Table 3.2 presents the monthly pair-wise returns correlation between all variables of interest along the entire sample period. The evidence presented in Table 3.2 further substantiates the interrelation between the unconditional volatility in the commodity markets themselves (e.g maize and soybeans). Specifically, Table 3.2 shows that the only statistically significant return correlation among commodity is that between maize and soybean during the entire sample. This is not surprising, since it is expected that the factors or events driving these commodity markets are likely to be very similar.

Table 3.2: *Pearson's Correlation Matrix of Monthly Returns (1982:01 - 2012:12)*

	Maize	Sugar	Soybean	Oil	Exchg.Rate	Int.Rate	Glob.Econ.Actv.
Maize	1						
Sugar	0.027	1					
Soybean	0.594***	0.003	1				
Oil	-0.065	-0.022	0.021	1			
Exchg.Rate	-0.054	-0.104**	-0.178***	-0.155***	1		
Int.Rate	-0.158***	0.019	-0.172***	-0.356***	0.200***	1	
Glob.Econ.Actv.	0.015	-0.037	0.024***	0.201*	-0.102	-0.0421	1
No. Observ	370	370	370	370	370	370	

Notes: Significance at the the 1%, 5% and 10% level are denoted by (***), (**) and (*) respectively.

On the other hand, Table 3.2 does not show evidence of pair-wise correlation between crude oil and any of the commodities price returns. Crude oil returns, however, are strongly correlated with macroeconomic factors. For example, we find all commodity prices and crude oil returns to be negatively correlated with the return on the indexed U.S. exchange rate and return real three month interest rate (except for sugar). Similarly, it appears that the global economic activity index is somewhat correlated with crude oil returns and less so with soybean but not statistically significant with regards to the remaining commodity return series. By no means these are simple correlations indicative of a causal effect among these return prices. However, at first glance it appears that there exists substantial evidence supporting the interdependence volatility transmission between commodity markets and economic fundamentals and less transmission between commodity markets themselves than argued in the literature.

Table 3.3 provides descriptive summary statistics of all the return series across the sample period. At first glance the mean return for sugar is the highest among the commodity series followed by oil, maize and soybean individually. The mean return of oil is approximately 1.6 times higher than maize and 3.5 times than soybean, but about only half of the sugar returns. The return on each of these markets in the effective period has only been negative for sugar returns with approximately -0.240 % while for maize, soybean and oil has been 0.083 %, 0.037 % and 0.139 % respectively. Additionally, the series presents evidence of non-normality evidenced by the excess skewness and kurtosis that all the series suffer from and formally by the Jarque-Bera statistic which rejects the null hypothesis of a normal distribution for all the series or that the joint hypothesis of the skewness and excess kurtosis being zero. Particularly, all series present significant evidence of skewness and kurtosis (all well above 3). Consequently, in the estimation of the GARCH and cDCC models we use a $Student's - t$ density distribution for the residuals. Moreover, all the return series show stationary properties as shown in Table 3.4. The results from a battery of unit root tests (with both non-stationarity and stationarity as the null hypothesis) are presented and all the evidence supports that all return series are stationary.

Table 3.3: *Summary Statistics and Unit Root Tests of Monthly Returns (1982:01 - 2012:12)*

	Maize	Sugar	Soybean	Oil	Exchg.Rate	Int.Rate	Glob.Econ.Actv.
Mean	0.083	-0.240	0.037	0.139	-0.052	-0.002	-0.084
Median	0.007	0.266	-0.046	0.405	-0.011	-0.002	0.256
Maximum	28.005	37.569	24.593	43.936	5.535	5.748	36.476
Minimum	-25.098	-32.001	-25.341	-29.523	-3.795	-3.561	-41.063
Std. Dev.	0.057	0.100	0.056	0.079	0.013	0.011	0.067
Skewness	-0.049	0.101	0.130	0.037	0.202	1.143	-0.849
Kurtosis	6.579	3.958	6.019	6.769	4.069	9.402	12.185
Jarque-Bera	197.623***	14.774***	141.539***	219.106***	20.135***	712.411***	1345.078***
Sum Sq. Dev.	1.202	3.684	1.150	2.283	0.061	0.042	1.659
Observations	370	370	370	370	370	370	370

Notes: Significance at the the 1%, 5% and 10% level are denoted by (***), (**) and (*) respectively.

Table 3.4: *Unit Root Tests of Monthly Returns (1982:01 - 2012:12)*

	Maize	Sugar	Soybean	Oil	Exchg.Rate	Int.Rate	Glob.Econ.Actv.
Test for Stationarity							
ADF (M1 - MAIC)	-14.611***	-14.196***	-14.506***	-14.316***	-13.460***	-28.549***	-13.744***
ADF (M2 - MAIC)	-14.520***	-14.170***	-14.750***	-14.300***	-13.460***	-28.510***	-13.720***
DF-GLS (ERS-MAIC)	-9.457***	-6.974***	-12.463***	-2.358**	-1.887*	-9.689***	-3.746***
KPSS (Bartlett Kernel)	0.126	0.078	0.072	0.215	0.125	0.016	0.131

Notes: Significance at the the 1%, 5% and 10% level are denoted by (***), (**) and (*) respectively.

3.5 Empirical Analysis

In this section we present the results from the VAR-cDCC-MGARCH models and then determine whether these conditional correlations have suffered form any significant changes across the sample period. This section is organized as follows. In the first part we will provide an analysis of the estimated conditional variances among the agricultural commodities and together with those variables of interests (e.g. crude oil and macroeconomic variables). Secondly, we will present the results from the three VAR-cDCC-MGARCH models. Finally, in this phase we will endogenously estimate any structural changes in the estimated dynamic correlations.

3.5.1 Conditional Variance

Figures 3-5-3-7 contain the conditional variance between of all three agricultural commodities over time. Figures 3-5 show the conditional variance of maize and soybeans in the same figure along the entire period. Maize prices displayed a relatively low levels of conditional variance for approximately fifteen years from the early 90's to just before the 2007/08 commodity price boom. Nevertheless, maize prices present several volatility clusters with peaks particularly visible during the 1998, 1997 and just after the financial crisis of 2008. Soybeans conditional variance also presents a similar stable period as maize, with peaks around 1983, 1988 and 2008. Overall, this pair of commodities appears to show several common periods of conditional variance; however, soybeans conditional variance is not as pronounced as it is in the case for maize during and after the 2007/08 period.

Figure 3-5: *Conditional variance of Maize and Soybeans price returns (1982:01-2012:012)*

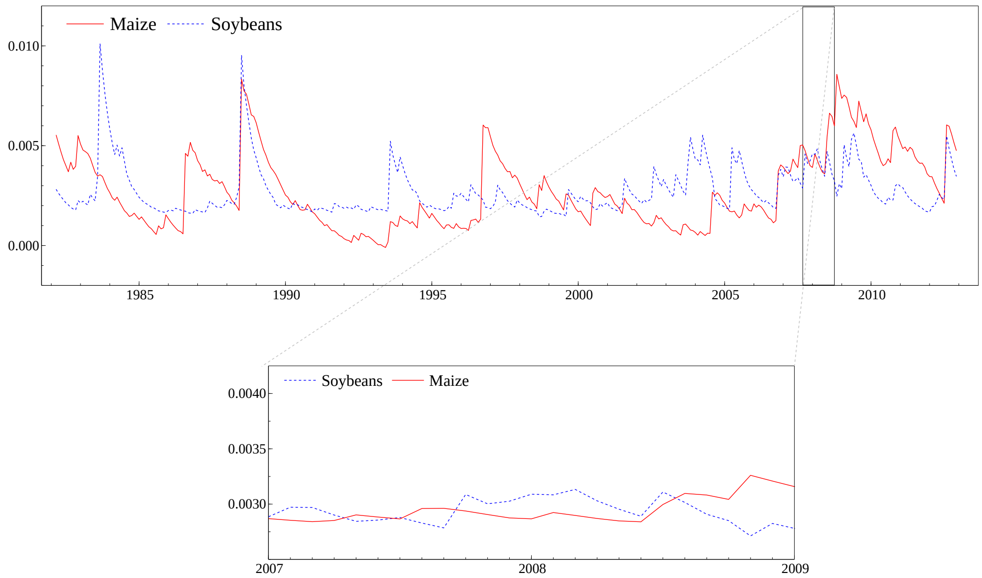


Figure 3-6: *Conditional variance of Maize and Sugar price returns (1982:01-2012:012)*

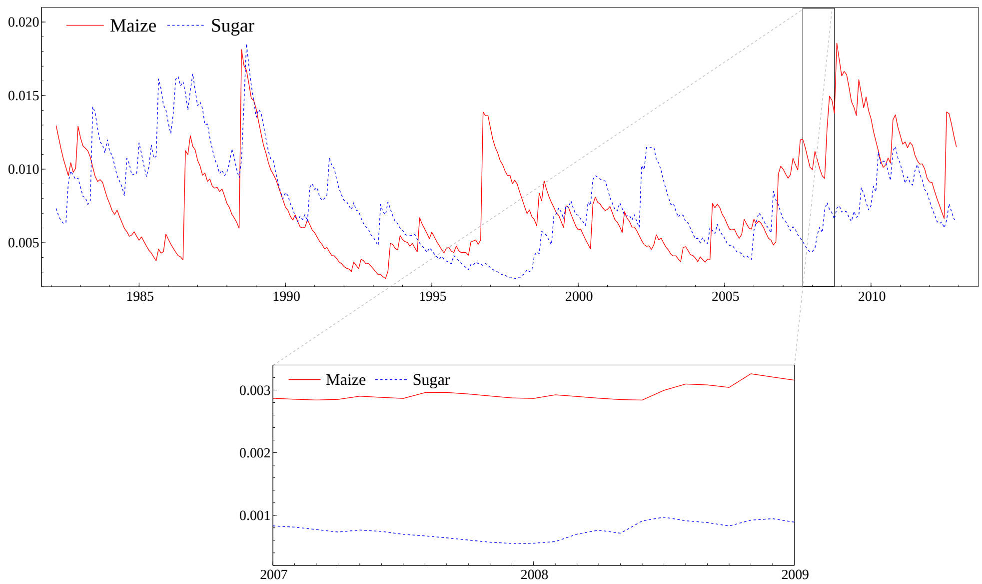
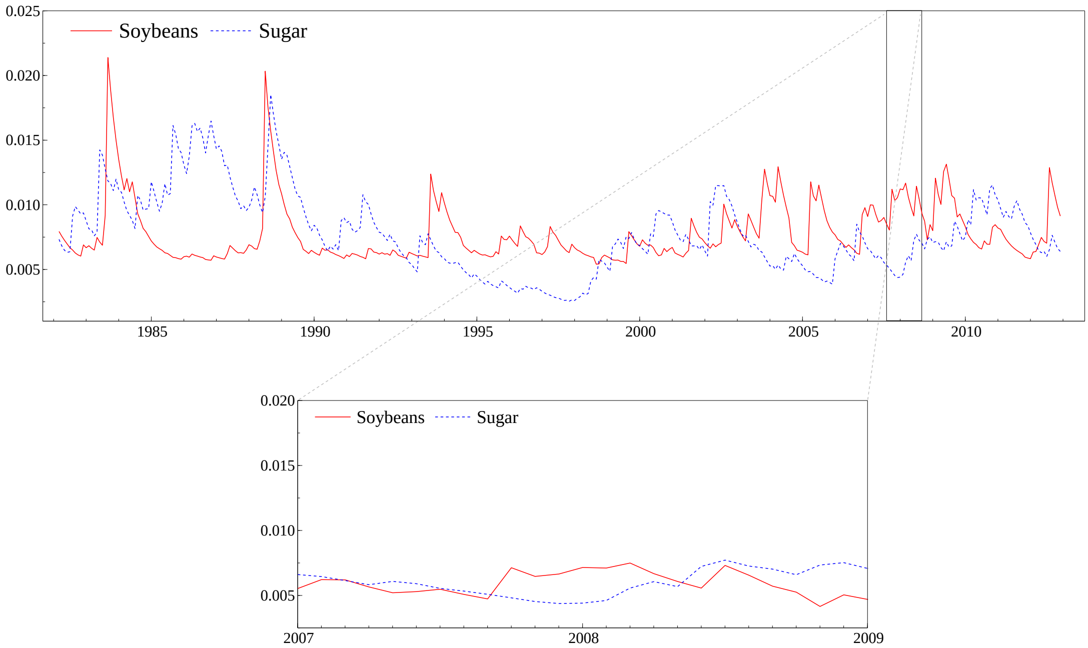


Figure 3-7: *Conditional variance of Soybeans and Sugar price returns (1982:01-2012:012)*

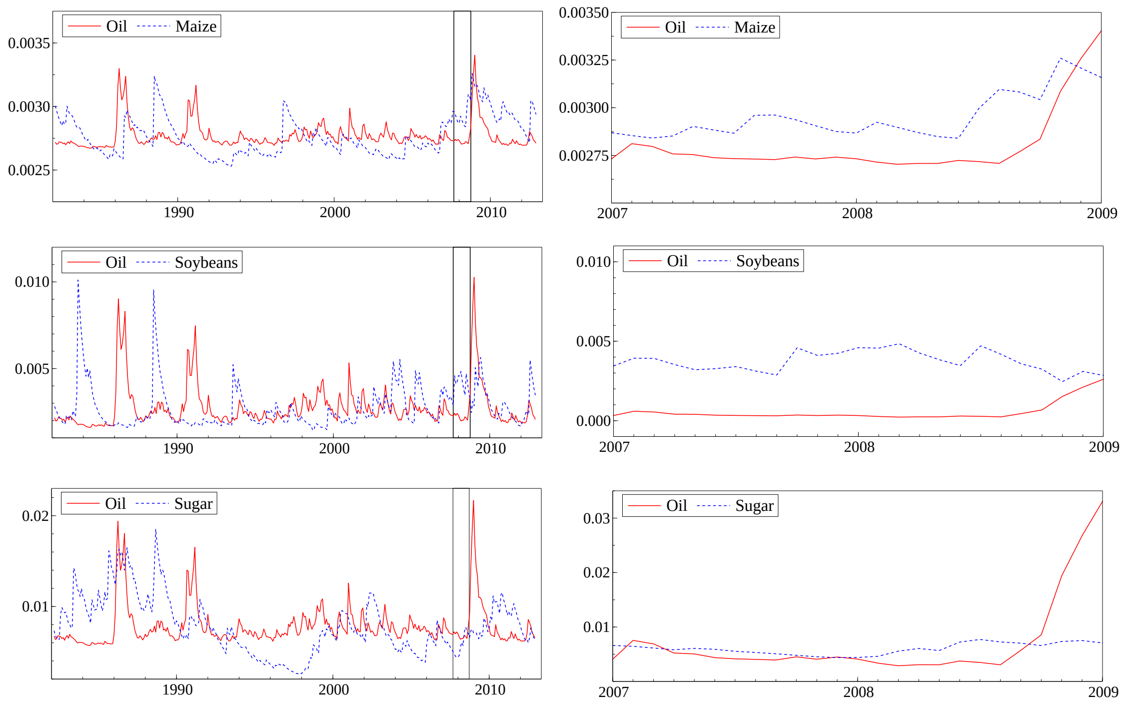


One possible explanation for this might be the adoption of the biofuel mandates by the U.S. in late 2004 in conjunction with other market instability characterized during this period, which increased the uncertainty around maize prices. This is likely to have affected maize rather than soybeans markets since it is maize the main input into the production of ethanol and not soybeans, which instead is used for biodiesel production. On the other hand, Figures 3-6-3-7 show the conditional variance development of maize and soybeans with sugar prices along the the same period. In this case, sugar prices only exhibit periods of high conditional variance before 1988 and relatively low levels of price instability thereafter; although the conditional varince increased (relative to the previous period) after the year 2000, but then decreased shortly after. Contrary to the case of both maize and soybeans markets, the conditional variance in the sugar market was not present around the 2008 financial crises, but common peaks with the these commodities are observed during the 1988 period.

In summary, Figure 3-5 and Figure 3-7 show that in comparison to all these three series, sugar prices present the lower conditional variance during this time period, particularly in the last two decades. Soybean prices series presents the highest number of instability events than these three agricultural commodities with a common peak for all around 1988. The instability observed in the soybeans market might be attributed to the fact that soybeans is a more internationally traded commodity and thus is more susceptible to a wider range of market forces than maize and sugar prices are not. Moreover, all three commodities, except for sugar prices, present a relatively significant level of persistence in their conditional variance along this period. In conclusion, from these figures, it is evident that maize and soybean price volatilities follow very similar market signals (with some exceptions) particularly when we focus on the major volatility clusters of 1988 and that after the 2008 financial crisis.

The apparent volatility spillovers from energy to agricultural commodity markets is a central question in the empirical literature and that of our research. Therefore, we turn the attention to the conditional voriance between crude oil and our three agricultural commodities. Figure 3-8 graphs the pair of the conditional variance between crude oil prices with each individual commodity along the same time period. From Figure 3-8, it is evident that crude oil price volatility reacts to energy market specific shocks with significant peaks around the years 1986, 1990 and after the 2008 financial crisis. It is only during the period during the financial crisis that we see crude oil price volatility coincide with movement in the maize and soybean markets, but crude oil exhibits a higher degree of price instability than any of the these commodities and the timing is not precisely the same. This graph along, raise doubts on the claim of volatility spillover from crude oil to these commodities, but this will be explored in more detailed when we present the results from the conditional correlation models.

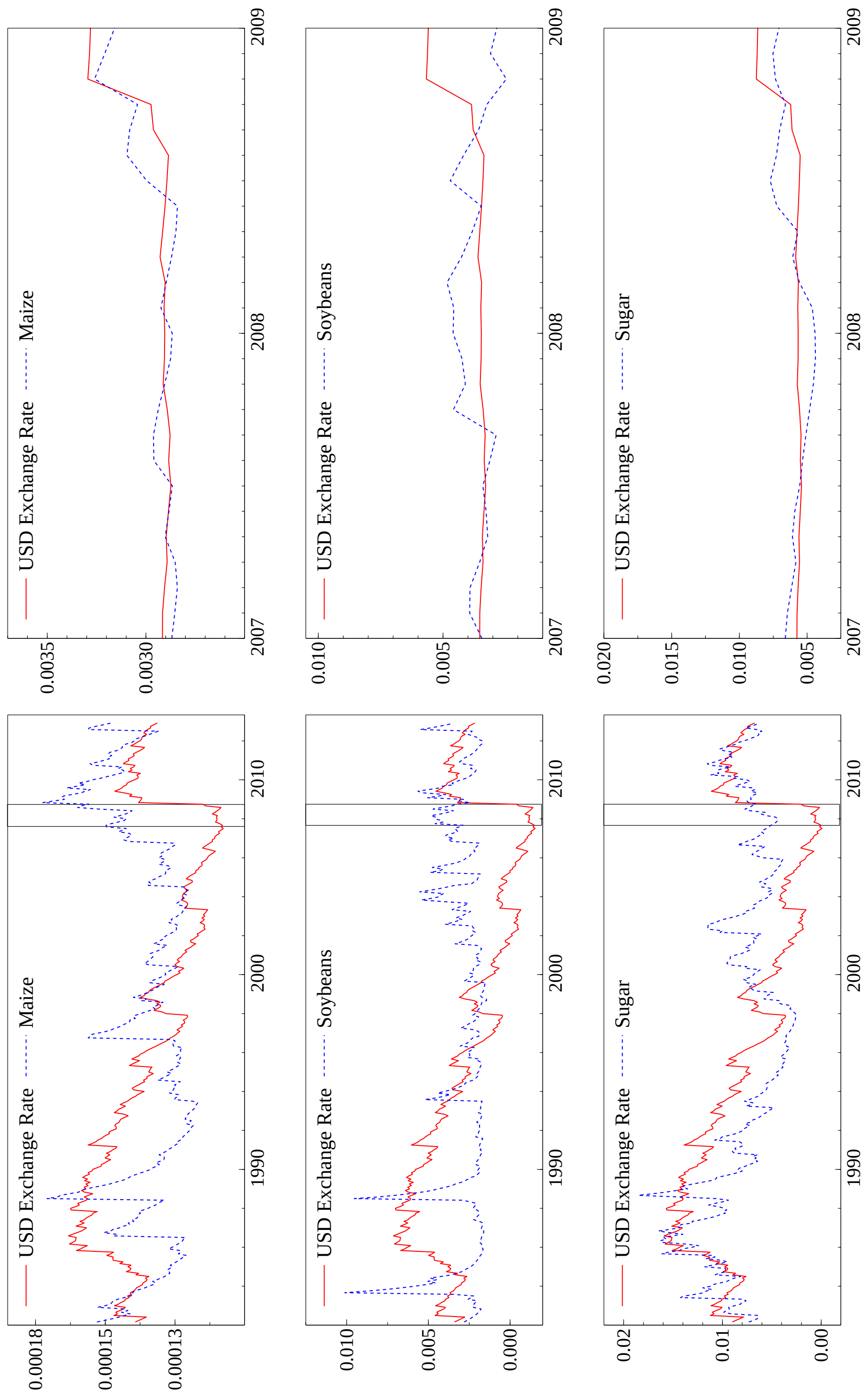
Figure 3-8: *Conditional variance of Crude Oil with the commodity price returns (1982:01-2012:012)*



Similarly, Figure 3-9 graphs the pair of conditional variance between the U.S. exchange rate and the agricultural commodity prices. In this case, the U.S. exchange rate conditional variance presents stable, but persistent levels of relative high conditional variance during the decade of the 80's with respect the more recent years. The conditional variance of this series reached its lowest level just before the 2008 financial crisis when then after a visible spike is present. Overall, it is evident that fluctuations in the conditional variance of the U.S. exchange rate are not related to movements of any of the commodities conditional variance. On the other hand, Figure 3-10 shows similar graphs, but this time between the conditional variance of the short term interest rate and the commodity prices. Here however, there seems to appear some common peaks of the conditional variance of the interest rate and the commodities particularly between soybeans and sugar after the 2000's and less evident with sugar. This observation is significant since it sheds light to the argument of the financialization of commodities during this time period and the effect it had on the instability of commodity markets.

Finally, Figure 3-9 show the conditional variance of crude oil prices paired with all three macroeconomic variables. In this case, it is evident the direct volatility spillovers between crude oil price returns and all macroeconomic variables during the 2008 financial crisis. The Killian index for global economic activity and the U.S. exchange rate exhibit high conditional variance than crude oil price returns during the entire sample, except during the 2008 financial crisis. Interest rate conditional variance show higher fluctuations in the conditional variance than crude oil does during the early 2000's; however, the 2008 episode appears to show a similar pattern with in the pair conditional variance behavior. Thus, Figure 3-9 shows that, and as opposed to the agricultural commodities evidence, crude oil presents a direct volatility link with macroeconomic variables.

Figure 3-9: *Conditional variance of USD exchange rate with the commodity price returns (1982:01-2012:012)*



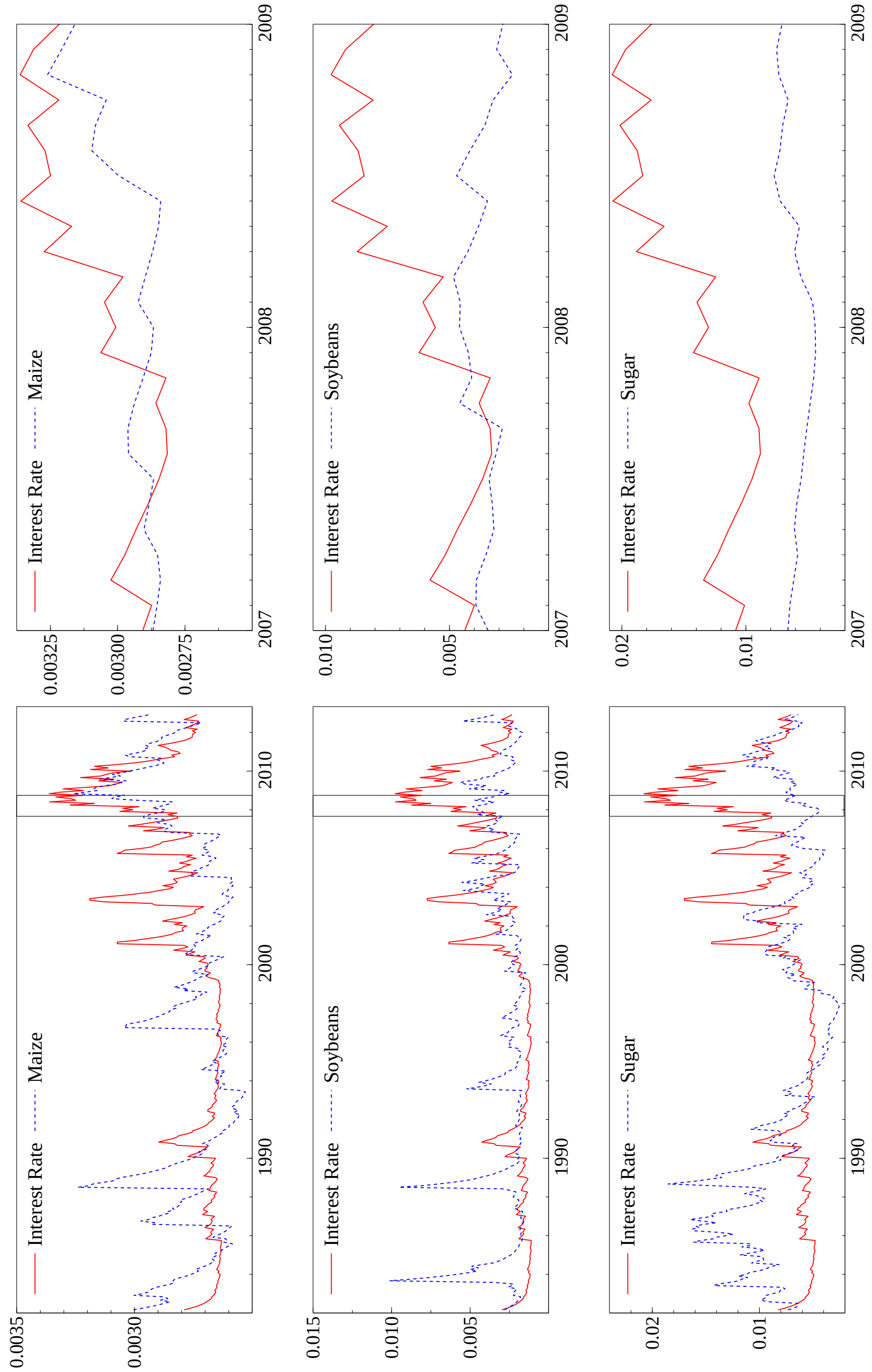
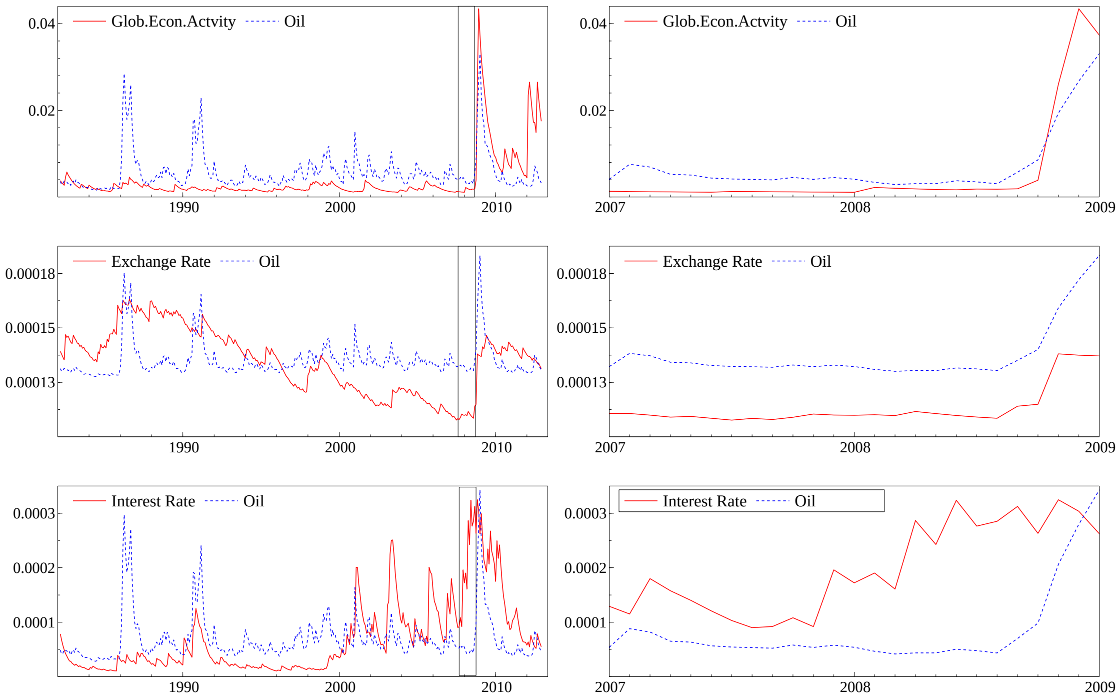


Figure 3-10: *Conditional variance of Interest Rate with the commodity price returns (1982:01-2012:012)*

Figure 3-11: *Conditional variance of Crude Oil price returns with Macroeconomic variables (1982:01-2012:012)*



3.5.2 Results of VAR-cDCC-MGARCH

In order to estimate the VAR-cDCC-MGARCH we apply three separate models corresponding to each one of the commodities of interest (e.g. maize, soybeans and sugar) with crude oil price returns and the macroeconomic factors. There are two reasons why we have decided to estimate these in three different models. In the first case we experience the limitations of the cDCC models with large numbers of parameters being estimated simultaneously [4]. Secondly, we are not interested in the cross conditional correlation between the agricultural commodities, but in the interdependence between these and crude oil price returns and the macroeconomic factors.

[4] As it is, the system has five variables and if including them all (e.g. the three commodities, oil and three macroeconomic factors) will be a system of seven variables and the likelihood function was not able to find a convergence solution.

Table 3.5: *Dynamic Correlation cDCC (1,1) for Maize*

	Maize	Oil	Exchg.Rate	Int.Rate	Glob.Econ.Actv.
Maize					
Oil	-0.070				
Exchg.Rate	0.000	-0.120*			
Int.Rate	-0.050	-0.490***	0.151**		
Glob.Econ.Actv.	-0.060	0.097	-0.030	-0.080	
α	0.013*				
β	0.937***				
Hosking's	Hosking (5)	101.967			
	Hosking (10)	220.702			
Li and McLeod's	Li-McLeod (5)	102.262			
	L i-McLeod (10)	221.176			

Notes: Significance at the the 1%, 5% and 10% level are denoted by $^{(***)}$, $^{(**)}$ and $^{(*)}$ respectively.

The results from the estimations of the cDCC models are presented in Tables 3.5−3.7, which have been estimated in two steps. In the first step we estimate the univariate part of the model and are presented in Tables 3.8−3.10. The univariate estimations are defined by an ARMA(p, q) process in order to capture the serial correlation in the residuals and a GARCH$(1, 1)$ specification with specific parametric forms for the conditional heteroskedasticity in order to capture the serial correlation in the residuals (See Table A.1 in Appendix A). In the second step, we estimate all the parameteres simultaneously, by maximizing the log-likelihood function assuming a student's-t distribution given that all variables suffer from excess kurtosis. This approach allows us to capture volatility clustering in commodity markets where we are more likely to observe high volatility at time t if it was also high at time $t-1$.

Table 3.6: *Dynamic Correlation cDCC (1,1) for Soybeans*

	Soybeans	Oil	Exchg.Rate	Int.Rate	Glob.Econ.Actv.
Soybean					
Oil	-0.030				
Exchg.Rate	0.130**	-0.120*			
Int.Rate	-0.080	-0.480***	0.158**		
Glob.Econ.Actv.	-0.020	0.096	-0.040	-0.080	
α	0.012*				
β	0.940***				
Hosking's	Hosking (5)	99.189			
	Hosking (10)	233.881			
Li and McLeod's	Li-McLeod (5)	99.507			
	Li-McLeod (10)	233.975			

Notes: Significance at the the 1%, 5% and 10% level are denoted by $^{(***)}$, $^{(**)}$ and $^{(*)}$ respectively.

Table 3.7: *Dynamic Correlation cDCC (1,1) for Sugar*

	Sugar	Oil	Exchg.Rate	Int.Rate	Glob.Econ.Actv.
Sugar					
Oil	-0.020				
Exchg.Rate	-0.080	-0.120**			
Int.Rate	0.034	-0.490***	0.166**		
Glob.Econ.Actv.	-0.100*	0.110*	-0.050	-0.090	
α	0.013*				
β	0.899***				
Hosking's	Hosking (5)	115.518			
	Hosking (10)	223.876			
Li and McLeod's	Li-McLeod (5)	115.653			
	Li-McLeod (10)	224.385			

Notes: Significance at the the 1%, 5% and 10% level are denoted by $^{(***)}$, $^{(**)}$ and $^{(*)}$ respectively.

The lag coefficients of the ARMA models for the univariate estimations are chosen by the AIC as well as the lagrange multiplier (LM) test for autocorrelation in the residual and square residuals (See Table A.1) and the results for all three univariate models are presented in Tables 3.8−3.10. Table 3.8 presents the simultaneous estimation of the univariate parameters for maize, crude oil price returns and the macroeconomic factors (i.e. Maize). In this model, both maize and crude oil show evidence of autoregressive and moving average behaviour in the returns series, which is consistent with the volatility clustering observed in commodity markets. On the other hand, the macroeconomic variables (i.e. exchange rate, interest rate and the Kilian Index) also show evidence of autoregressive and moving average behavior, but to a lesser extent. Moreover, in neither of these cases does there exists evidence of drifting in the return series since the constant in the mean equation is not significant for any of these variables.

In order to simultaneously estimate all the parameters from Maize, we must correctly specify the univariate GARCH process for each variable. From Table 3.8, we see that the best fitted model (based on the AIC) for maize is a GARCH$(1,1)$ and for crude oil it is an APARCH specification. For maize, α which captures the influence of new shocks on volatility is are significant for the case of oil price returns. One explanation is that the rest of the variables are modeled using GJR-GARCH (e.g. Kilian Index and interest rates) and this type of model assumes that not all shocks have the same influence on the price return (i.e. leverage effect). On the other hand, the parameter β, which captures the persistence of volatility shocks or the impact of the own-variance on volatility development, is positive and statistically significant at the 1% level in all variables estimated. The value of β for maize is about 0.94, which indicates that old shocks to the maize price returns are rather persistent and long lasting. On the

Table 3.8: *Univariate Estimation Results for Maize of the MGARCH - Model 1*

	AR(1)	**AR(2)**	**AR(3)**	**MA(1)**	**MA(2)**	ω	α	β	γ	δ
Glob.Econ.Actv.[1]										
Coeff.	1.278***	-0.451***	0.115**	-0.958***		1.243	0.010	0.859***	0.189*	
S.E.	0.057	0.090	0.055	0.023		0.983	0.016	0.082	0.105	
Int. Rate[1]										
Coeff.	0.388***	-0.043	0.054	-0.969***		0.012**	0.033	0.836***	0.243***	
S.E.	0.056	0.057	0.049	0.013		0.006	0.033	0.048	0.062	
Exchg. Rate[2]										
Coeff.	-0.392***	0.094	-0.021	0.735***		0.006	0.007	0.988***		
S.E.	0.118	0.074	0.069	0.108		0.016	0.012	0.019		
Oil[3]										
Coeff.	-0.39**			0.512***	-0.050	0.004	0.183***	0.750***	0.264*	1.188***
S.E.	0.201			0.194	0.060	0.004	0.050	0.060	0.151	0.310
Maize[2]										
Coeff.	-0.64***	0.177***		0.889***		1.503	0.007	0.937***		
S.E.	0.081	0.050		0.082		1.075	0.013	0.038		
No. Observations :	370									
Log Likelihood :	4189.299									

Notes: Significance at the the 1%, 5% and 10% level are denoted by $^{(***)}$, $^{(**)}$ and $^{(*)}$ respectively.

[1] GJR-GARCH(1,1): $h_t = \omega + \alpha\epsilon_{t-1}^2 + \beta h_{t-1} + \gamma\epsilon_{t-1}^2 I_{\{\epsilon_{t-1}\geq 0\}}$;

[2] GARCH(1,1): $h_t = \omega + \alpha\epsilon_{t-1}^2 + \beta h_{t-1}$;

[3] APARCH(1,1):$h_t^\delta = \omega + \alpha\left[|\epsilon_{t-1}| - \gamma_1\epsilon_{t-1}\right]^\delta + \beta h_{t-1}^\delta + \gamma\epsilon_{t-1}^2$

Table 3.9: *Univariate Estimation Results for Soybean of the MGARCH - Model 2*

	AR(1)	**AR(2)**	**AR(3)**	**MA(1)**	**MA(2)**	ω	α	β	γ	δ
Glob.Econ.Actv.[1]										
Coeff.	1.255***	-0.42***	0.108*	-0.95***		1.263	0.009	0.857***	0.200*	
S.E.	0.061	0.096	0.058	0.028		1.006	0.016	0.082	0.112	
Int. Rate[1]										
Coeff.	0.386***	-0.040	0.062	-0.97***		0.011**	0.033	0.838***	0.231***	
S.E.	0.056	0.058	0.050	0.013		0.006	0.035	0.048	0.059	
Exchg. Rate[2]										
Coeff.	-0.38***	0.088	-0.020	0.723***		0.005	0.009	0.986***		
S.E.	0.114	0.071	0.066	0.104		0.013	0.009	0.013		
Oil[3]										
Coeff.	-0.380			0.508**	-0.040	0.004	0.188***	0.739***	0.245*	1.188***
S.E.	0.253			0.241	0.066	0.004	0.052	0.063	0.149	0.305
Soybeans[1]										
Coeff.	0.590**	-0.150		-0.300		2.390**	0.145**	0.843***	-0.159***	
S.E.	0.241	0.095		0.237		0.987	0.067	0.049	0.078	
No. Observations :	370									
Log Likelihood :	4189.299									

Notes: Significance at the the 1%, 5% and 10% level are denoted by $^{(***)}$, $^{(**)}$ and $^{(*)}$ respectively.

[1] GJR-GARCH(1,1): $h_t = \omega + \alpha\epsilon_{t-1}^2 + \beta h_{t-1} + \gamma\epsilon_{t-1}^2 I_{\{\epsilon_{t-1}\geq 0\}}$;

[2] GARCH(1,1): $h_t = \omega + \alpha\epsilon_{t-1}^2 + \beta h_{t-1}$;

[3] APARCH(1,1):$h_t^{\delta} = \omega + \alpha\left[|\epsilon_{t-1}| - \gamma_1\epsilon_{t-1}\right]^{\delta} + \beta h_{t-1}^{\delta} + \gamma\epsilon_{t-1}^2$

other hand and in relation to maize, crude oil shows a low own-variance impact (low β) and rather high sensitivity to external shocks to the market (high α). This combination of factors indicates that crude oil is more sensitive to external shocks during volatility phases than maize. Moreover, overall none of the sums between α and β are close to one (except perhaps for the exchange rate), which implies that compounded shocks to these series experience a decaying autocorrelation function. Furthermore, The asymmetry coefficient γ is positive and significant (at minimum to the 10% level) for all variables where GJR-GARCH was used (e.g. Kilian Index, interest rates and crude oil). For crude oil in particular, it indicates that shocks have an asymmetric effect on the volatility of crude oil prices. More precisely, it indicates (by the positive sign) that positive price shocks reduce volatility more than negative shocks[5] (See Mensi et al. [2015] for similar conclusions). Generally, the literature assumes that negative shocks increase volatility more than positive shocks do. However, a positive price shock to the oil price increases the production costs of all other goods and in turn induces a higher risk premium for holding stocks. Finally, the power coefficient δ in the APARCH specification used to model crude oil is significant at the 1% level.

Table 3.9 presents the simultaneous univariate parameter estimation results for soybeans (i.e. Model 2). For soybeans the best fitted model according to the AIC is a GJR-GARCH$(1, 1)$ and the same model specification used in Maize for the remaining variables. In this case, both α and β coefficients are significant for crude oil and soybeans. As before, the results indicate that soybeans (as it is the case for crude oil) is sensitive to external shocks relative to shocks to its own-variance. Additionally, the γ coefficient for the soybean GJR-GARCH model is statistically significant at the 1% level, suggesting an asymmetric effect on the

[5]The same implications apply to the remaining variables.

Table 3.10: *Univariate Estimation Results for Sugar of the MGARCH - Model 3*

	AR(1)	**AR(2)**	**AR(3)**	**MA(1)**	**MA(2)**	ω	α	β	γ	δ
Glob.Econ.Actv.[1]										
Coeff.	1.268***	-0.43***	0.108*	-0.96***		1.526	0.008	0.834***	0.218	
S.E.	0.058	0.093	0.058	0.024		1.299	0.017	0.105	0.136	
Int. Rate[1]										
Coeff.	0.375***	-0.030	0.054	-0.96***		0.011**	0.042	0.834***	0.222***	
S.E.	0.059	0.059	0.050	0.015		0.006	0.037	0.048	0.059	
Exchg. Rate[2]										
Coeff.	-0.41**	0.103	-0.030	0.746***		0.008	0.005	0.987***		
S.E.	0.159	0.084	0.074	0.147		0.019	0.014	0.025		
Oil[3]										
Coeff.	-0.37*			0.498**	-0.040	0.006	0.202***	0.730***	0.212	1.053***
S.E.	0.222			0.213	0.060	0.006	0.051	0.062	0.144	0.285
Sugar[2]										
Coeff.	0.822**	-0.600		-0.23*		0.000***	0.074**	0.910***		
S.E.	0.349	0.385		0.136		0.000	0.033	0.026		
No. Observations :	370									
Log Likelihood :	3992.379									

Notes: Significance at the the 1%, 5% and 10% level are denoted by $^{(***)}$, $^{(**)}$ and $^{(*)}$ respectively.

[1] GJR-GARCH$(1,1)$: $h_t = \omega + \alpha\epsilon_{t-1}^2 + \beta h_{t-1} + \gamma\epsilon_{t-1}^2 I_{\{\epsilon_{t-1}\geq 0\}}$;

[2] GARCH$(1,1)$: $h_t = \omega + \alpha\epsilon_{t-1}^2 + \beta h_{t-1}$;

[3] APARCH$(1,1)$:$h_t^\delta = \omega + \alpha\left[|\epsilon_{t-1}| - \gamma_1\epsilon_{t-1}\right]^\delta + \beta h_{t-1}^\delta + \gamma\epsilon_{t-1}^2$

volatility of soybean prices. The negative sign of the γ coefficient shows that negative shocks at time t_1 have a stronger impact in the variance at time t than positive shocks. Finally, Table 3.10 summarizes the results from the univariate parameter estimation results of using sugar (i.e. Model 3). Here, we found the best fitted model to be a GARCH $(1, 1)$ for sugar and the same as in the previous cases. The α and β coefficients are significant for sugar and crude oil and they indicate that sugar is more sensitive to shocks to its own-variance on volatility development than to external shocks (high β ralative to low α).

Tables 3.5−3.7 present the estimated parameters for the conditional correlations of the cDCC model. For Maize, α and β are statistically significant at the 10% and 1% level respectively. In this case, the fact that the β coefficient is higher than α suggests that the conditional correlation between the residuals is persistent to a higher degree. This is the case for both maize and soybeans models; however, we observe the opposite for the model using sugar return prices. Finally, there does not appear to be any sign of misspecification given that we fail to reject the null hypothesis of no cross-correlations in the squared residuals (Hosking's Multivariate test) and find no evidence of ARCH effects (Li and McLeod's test) in all three models.

The results from Tables 3.5−3.7 suggest that maize does not show any sign of strong conditional correlation with crude oil or any of the macroeconomic factors included. That is, the volatility episodes that we have described are related to commodity specific and are not directly correlated with those in the crude oil market or by macroeconomic variables. However, this does not imply that crude oil prices can determine these commodity prices in the long-run. As a matter of fact, we have shown in the previous chapter that there exists strong one-to-one long-run relationship between these markets. However, the interdependences between energy and these agricultural markets seems to be restricted to direct spillover effects particularly during and after the 2008 financial crisis.

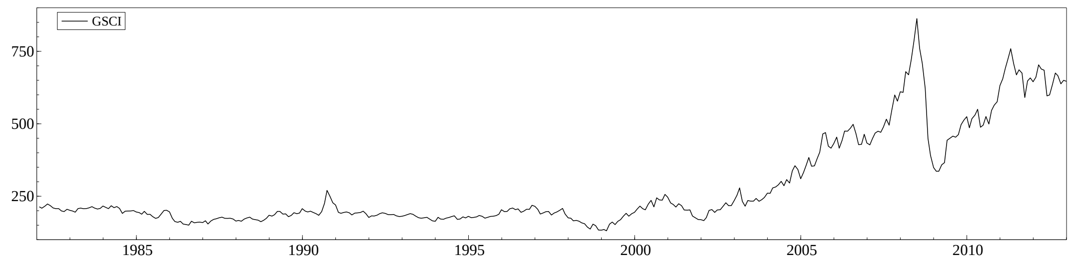
Succinctly, soybeans appears to be the only agricultural commodity to show strong and significant correlation with the U.S. exchange rate and none of these with crude oil and the remaining macroeconomic factors. On the other hand, sugar appears to be correlated with the global economic index given a significance level of 10%, but the sign is negative. Crude oil prices, present a strong and negative correlation with the exchange rate and interest rate as well as a significant correlation at the 10% level with the global economic activity index. Finally, both the interest rate and exchange rate have a strong and positive correlation across all three models at the 5% significance level. Nevertheless, the results indicate that instability periods in these commodities are not associated with instability in macroeconomic fundamentals or crude oil market.

So far, we have shown that macroeconomic variables and crude oil price returns cannot be linked with periods of volatility in the commodity markets. Then, if economic fundamentals do not present a significant link with commodity markets one might argue that these periods of instability might be due to anything that cannot be explained by these variables. Since the 2007/08 commodity price shock there has been an extensive interest in the literature on the effects of the financialization of commodity markets had on this period. Consequently, economists and policy makers alike have tried to understand of there exists any causal relationship between financial and commodity markets particularly during and after the 2007/08 price shock. However this literature has been constrained by the data availability and the debate grows when researchers try to define agents with commercial from financial or speculative positions. Nevertheless, there exists a general consensus that, despite the possible causal links between the financialization of commodity markets and commodity prices, the primary source of commodity price drivers are factors derived from demand and supply sides. This is also corroborated in the findings from the first chapter where commodity prices are affected by macroeconomic variables and crude oil in the long-run. However, very few studies have attempted to understand the volatility links between the financialization of commodities and these markets.

As a consequence, we have decided to simultaneously estimate these variables and in addition include the return to the Bloomberg Commodity Index in order to capture any links between commodity index investment had an impact on spot volatility in commodity markets. Additionally, a number of studies have used these index funds to evaluate speculation and bubble formations in commodity futures and spot prices (See for example, Irwin and Sanders [2011], Creti et al. [2013], Büyükşahin and Robe [2014] and Basak and Pavlova [2015a]). The mechanism through which investment in futures indices affects volatility in the spot market is not clear and highly debated in the literature. However, the fact that futures prices are a shadow of spot prices through the standard no-arbitrage relation lead us to link these two markets very closely. One way in which this channel takes effect is through the high appetite by investors in commodity futures markets. Demand in the futures market increase the price of these contracts and signals a stronger global economy which in turn motivates each goods producer to demand more of the commodity for producing more. Through this same mechanism, noise from the future market can feed into the spot market and consequently increase its volatility.

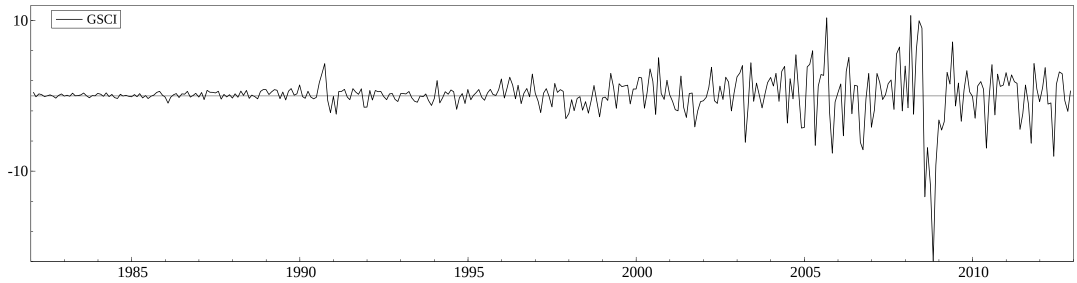
The Bloomberg Commodity Index index uses a weighted methodology based on 1/3 world production value and 2/3 market liquidity which contains 22 exchange-traded futures on physical commodities (e.g. crude oil, maize, soybean and sugar) and is rolled forward from the fifth to the ninth business day of each month. This commodity price index was value at 100 in December 1990 and introduced to the market in January 1998[6]. The aim from using this variable in the analysis is to be able to capture any correlation between the financialization and food commodity volatility from 1991 to 2012.

Figure 3-12: *Bloomberg Commodity Index - Levels (1982:01-2012:012)*



[6]The only reason for using this commodity price index and not another is the availability of data and the length of the series. Other commodity indexes begin in the late 1990's.

Figure 3-13: *Bloomberg Commodity Index - Returns (1982:02-2012:012)*



In Table 3.11 we present the results from the simultaneous cDCC (1,1) model including the return on the Bloomberg Commodity Index using the dame data series and frequency from January 1991 to December 2012. The results from this model are remarkably similar to those presented in Tables 3.5-3.7. The only exception is the conditional correlation between soybeans and the exchange rate which magnitude is similar to that presented in Table 3.6, but the sign of the conditional correlation is the opposite. However, this can be explained by the instability period (discussed in greater detail in the next section) between the return price to soybeans and the U.S. exchange rate from the mid 1990's until early 2000's where the conditional correlation was significantly lower (negative) during this period. Nevertheless, the important realization from this model is the strongly significant and positive correlation between the return to the Bloomberg Commodity Index with the return to all commodity prices (including oil) during this period. Thus, from this evidence it appears that, more than economic fundamentals, it is the commodity price index that is associated with periods of instability in the agricultural commodity markets. In addition to this, we are also able to determine that returns in the commodity markets are highly associate with the same fluctuations in the other commodity markets. For example, we see that the conditional correlation between maize and soybean to be approximately

0.5 during this period, which reinforces that these commodities share a great deal of factors in their price return co-movements.

Table 3.11: *Dynamic Correlation cDCC (1,1) for all variables*

		Bloomberg	Glob.Econ.Actv	Int.Rate	Exchg.Rate	Oil	Maize	Soybean	Sugar
Bloomberg		1							
Glob.Econ.Actv		0.109	1						
Int.Rate		-0.377	-0.053	1					
Exchg.Rate		-0.262***	-0.006	0.203***	1				
Oil		0.535***	0.141$^{(**)}$	-0.575***	-0.180**	1			
Maize		0.227***	-0.119	-0.080	-0.080	-0.074	1		
Soybean		0.289***	-0.075	-0.103	-0.191**	-0.026	0.576***	1	
Sugar		0.095***	-0.100	0.043	-0.068	-0.058	0.123*	0.145**	1
α	0.008								
β	0.910***								
Hosking's	Hosking (5)	311.364							
	Hosking (10)	622.187							
Li and McLeod's	Li-McLeod (5)	311.953							
	Li-McLeod (10)	623.120							

Notes: Significance at the the 1%, 5% and 10% level are denoted by $^{(***)}$, $^{(**)}$ and $^{(*)}$ respectively.

In summary, from Table 3.11 it is evident that economic fundamentals are not able to explain the price instability in the commodity markets. Yet, it is only the return commodity price index that is the only variable associated with periods of instability in the commodity markets. Although in this study we cannot claim causation, it is evident that activity in the futures market and the financialization of these commodities through the implementation of these commodity indexes is associated with the return price to these commodities. This conclusion is also supported by other authors in the literature such as Gilbert [2010], Tang and Xiong [2012a], Du et al. [2011], Tokis [2011],Girardi [2012], Pen and Sevi [2013] and more recently by Creti et al. [2013].

In the next section, we will determine any instability in the significant dynamic conditional correlations found in the estimated models presented in Tables 3.5-3.7.

3.5.3 Structural Changes in the cDCC Estimates

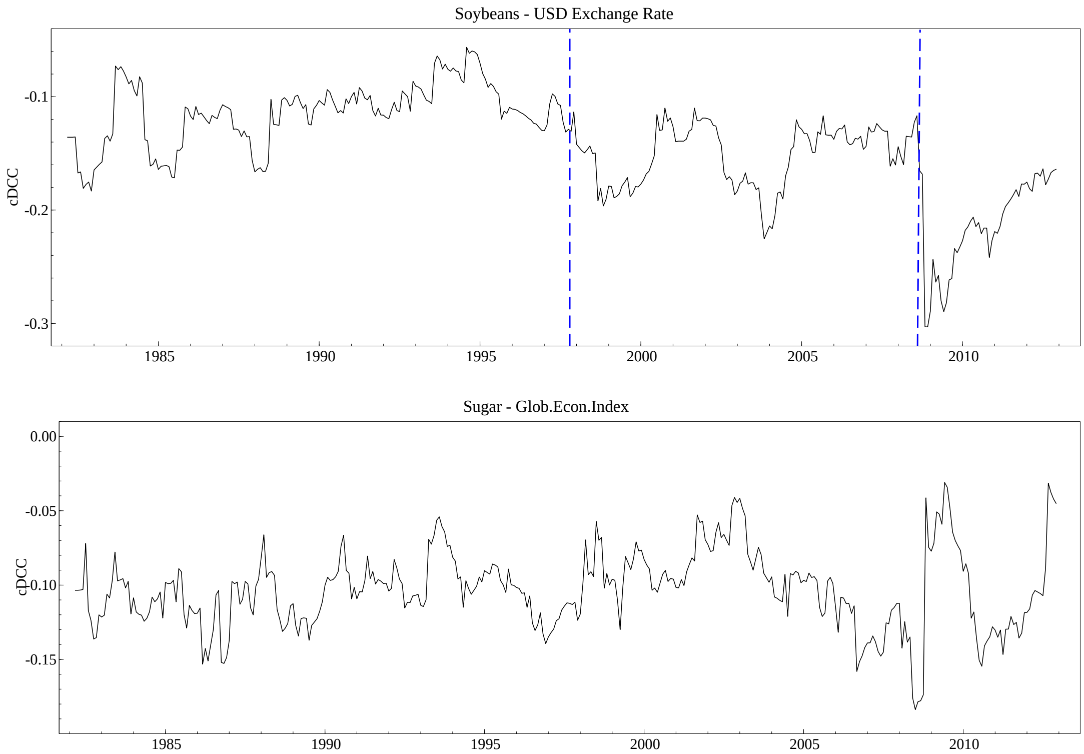
In order to estimate the structural changes in the dynamic correlations an endogenous approach developed by Lavielle [2005] has been used. In Figures 3-14-3-15 we present the results from applying the penalized contrast function to determine any shifts in both mean and variance of the dynamic correlations that had been found to be statistically significant during this time period.

In Figure 3-14 we show the results from the dynamic correlations between soybeans and the U.S. exchange rate (top) as well as that from sugar and the Kilian index (bottom). For the first conditional correlation, we observe that the dynamic correlation has had a negative trend from 1982 to 2012 with three regimes being detected. The first period is from January 1982 to October 1997, the second period from November 1997 to August 2008 and finally from September 2008 to the end of the sample in December 2012. All these shifts are associated with more negative correlations than the previous regime. The first shift in the dynamic correlation between soybeans and the U.S. exchange rate is detected during the Asian Financial Crisis of 1997, which also coincides with a period of high soybean prices. During this period, not only did the exchange rate between U.S. dollar and the ASEAN (Association of Southeast Asian Nations) countries dramatically fall, but also a combination of falling demand for soybeans from fast-growing economies in Asia together with record harvesting (due to the incentives of high global market prices for soybeans) in major global producers, fuel the instability in the soybean global market [Clay, 2014]. The second structural change in the dynamic correlation from these two variables is associated with the end of a period of historical commodity price increases and the financial crisis of 2008. This is a very interesting result since again the instability of the soybeans market is associated with major global macroeconomic events. The second graph (bottom) from Figure 3-14 corresponds to the dynamic correlations between sugar and the Kilian index. In this case, the relationship does not suffer from significant structural changes across the entire period and the conditional correlation remains negative along the sample.

Similarly, Figure 3-15 present the dynamic conditional correlations between the U.S. exchange rate and the short-term interest rate. As expected the relationship is positive and significant along the entire period. Also, it presents a stable relation up to July 2007 where we find the mean of the conditional correlation to be significantly higher then after. The conditional correlations here presented show the links between monetary policy and the response to this in the U.S. dollar foreign exchange market.

Finally, Figure 3-16 crude oil prices and all macroeconomic variables. The top figure shows the conditional correlation between crude oil price returns and the U.S. short term interest rate (3 Month T-Bill). In this case, and in this relationship we detect only one significant regime change at September 2007. The shift is associated with a more negative dynamic correlation than in the previous period. These results, to an extent, are remarkable since the full thrust of the financial crisis did not spread out through the economy until a year later and crude oil prices peaked by mid 2008 (about 10 months later). This date is associated with less than a month after the first decrease in the federal funds rate since mid 2003 by 50 basis points on August, 17 2007 and another 50 basis points

Figure 3-14: *Structural Changes of cDCC for Soybean and Sugar (1982:01-2012:012).*



by early September of the same year as well as a similar trends in the 3-Month Treasury Bill during this same period [FOC, 2007]. Additionally, the end of this period ends coincides with the beginning of the steepest price shock period until the end of the 2007/08 commodity price boom. It is evident that the increasing troubles of market liquidity together with historical high oil prices significantly raised the uncertainty in the markets during this period.

Figure 3-15: *Structural Changes of cDCC for USD Exchange Rate and Interest Rate (1982:01-2012:012).*

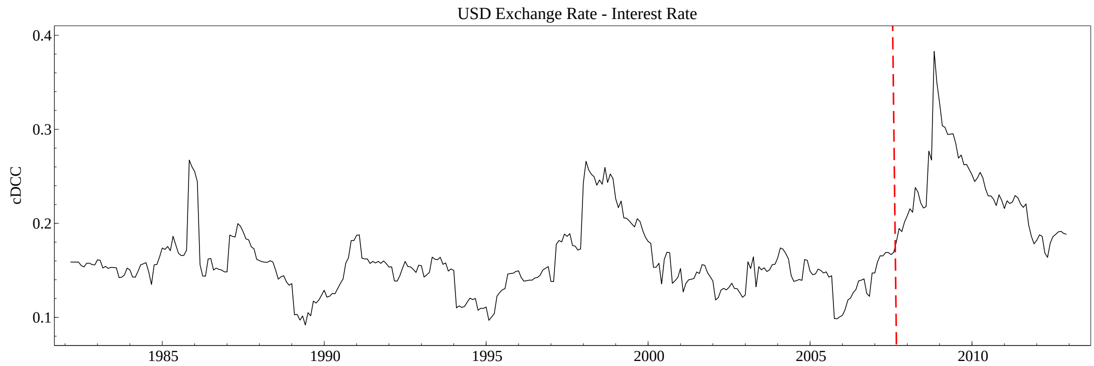
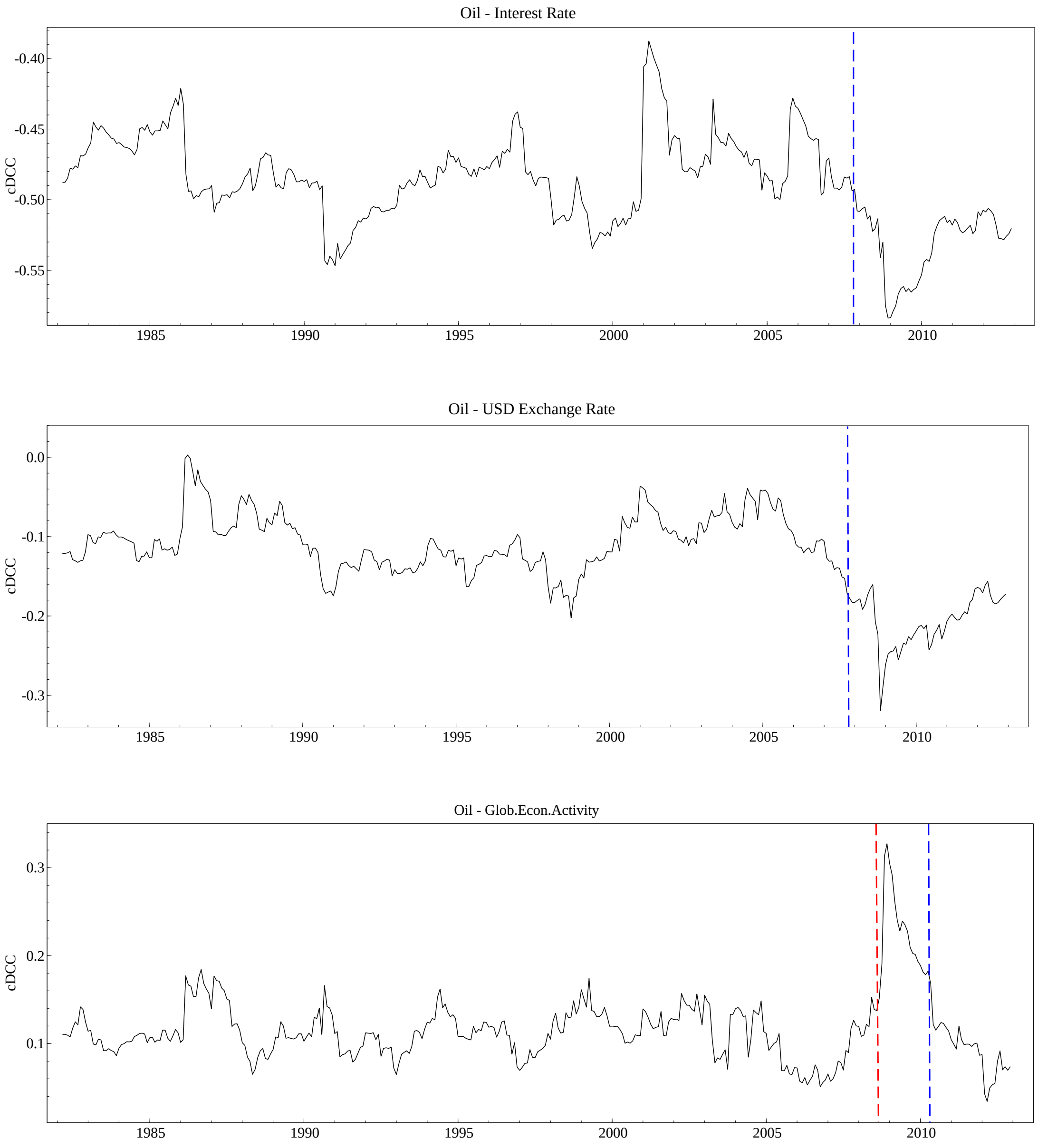


Figure 3-16: *Structural Changes of cDCC for Crude Oil with Macroeconomic variables (1982:01-2012:012).*



3.6 Discusion

In this section the empirical results will be presented and we will concentrate on the relationships which yield statistically significant results. From the results of Maize, in Table 3.5, we concluded that maize does not present any evidence of interdependence with any of the macroeconomic factors nor with crude oil price returns in the along the entire period. The fact is that from the univariate estimates, maize shows high persistence volatility shocks to its own-variance evolution. Thus, contrary to a number of findings in the literature, we cannot conclude that there exists any degree of interdependence between maize and crude oil price returns in the analyzed period. Thus, explaining the rise in maize volatility from the early 2000s to mid-2008, cannot be explained through its interdependence with crude oil and macroeconomic factors.

Soybean shows a similar behavior in relation to crude oil price returns, but we find statistically significant and negative dynamic correlation between the former and the U.S. exchange rate. Specifically, we determine a weak interdependence between soybean and the U.S. exchange rate during the sample. Moreover, we show that this correlation is far from being constant and determine three distinct periods in the relationship. In fact, the correlations between soybean and the U.S. exchange rate have become more negative with a substantial peak during the 2008 financial crisis. This relationship exhibits a clear pattern of interdependence particularly during the periods of economic instability. That is, during the period before the 1997 Asian Crisis, the correlation was less negative (just about -0.10) and somewhat stable. However, on the brink of the 1997 crisis the relationship collapses and a similar behavior is observed during the 2008 financial crisis. Due to the interdependence between the short-term interest rate and the U.S. exchange rate, we see that the soybean market presents a significant degree of interdependence with macroeconomic factors. These results are consistent with the empirical evidence of the long-run relationship between soybean and the U.S. exchange rate presented the previous chapter. One of the main implications from this result is that it is not possible to explain the rise in soybean prices solely on the basis of the weak interdependence with the U.S. exchange rate. Moreover, neither can it be explained through a stronger relationship with crude oil nor can it be explained by demand-side (e.g. Kilian Index) behavior of global markets.

Crude oil markets present a strong and significant interdependence with all macroeconomic factors. In terms of the relationship between crude oil and the U.S. exchange rate we determine a weak yet statistically significant correlation with five different periods along the sample period. The dynamic correlations in this relationship are not constant overtime and they exhibit patterns affected by global macroeconomic instability. In Tables 3.5−3.7 the dynamic correlations during non-crisis periods present a less negative (close to zero) correlations (see for example the 1990s). On the other hand, during the crisis periods the interdependence between crude oil and the U.S. exchange rate increases as evidence from the dynamic correlations become less negative particularly during the 2008 financial crisis. These results are not surprising and consistent across the empirical literature (See for example, Reboredo [2012], Turhan et al. [2014] and Mensi et al. [2015]).These results have a number of implications, one being that crude oil and the U.S. exchange rate present evidence of asymmetric dependence as crude oil price returns are more negatively linked with US dollar returns when the U.S. dollar depreciates, as compared to when it appreciates (See Chen and Khanna [2013] for similar results). Also, by looking at the interdependence between crude oil and the U.S. exchange rate alone, one cannot explain the price dynamics leading to the 2008 oil price shock. Moreover, one has to look at other macroeconomic determinants and demand-side factors in order to explain the oil price behavior during this period. This is, for example, the interdependence between crude oil returns and the Kilian index for global economic activity. This relationship presents a weak yet positive and constant interdependence. However, together with the U.S. exchange rate it cannot explain this exceptional period. The dynamic correlations between crude oil and the short term interest rate negative and has a strong degree interdependence across the entire sample. This relationship is very well explained by Taylor [2001] where the authors use an interest rate instrument set in response to inflation rates and output gap measures from (for example) an oil shock. In this model, the negative relationship is exemplified through a drop in the ex-ante real interest rate, stimulating aggregate demand and consequently an increase in the demand for energy [Krichene, 2006]. Thus, global macroeconomic factors present a strong interndependence with global crude oil price returns and represent fundamental determinant in global energy markets.

Additionally, from Table 3.11 the evidence is overwhelming in favor that the futures commodity price index and common market factors are closely related to the volatility in these commodity markets. Particularly, maize, soybean and sugar conditional correlations are positively and statistically significant associated with the return in the commodity price index. This evidence, in addition to the fact that none of the economic fundamentals indicate any relation with these commodities lead us to conclude that commodity index investment in agricultural commodities is very much interlinked with the instability of these during the analyzed period. Moreover, it is also particular in the crude oil market where the commodity price index is very much related to the commodity price index. Nevertheless, this results have been extensively argued and shown in the empirical literature and we also provide significantly evidence in favor of this argument.

Finally, a last, yet important, implication from our results is that only common shocks to these agricultural commodities seems to be correlated across time. Particularly this is the case between maize and soybeans. This is an indication that the sources of shocks for these commodities prices in levels and volatility are not the same. In the previous chapter, we concluded that macroeconomic variables and in particular crude oil prices have a permanent effect in the long-run prices of these commodities. On the other hand, in the current study we are unable to draw any meaningful correlation among these variables and the price volatility of maize and soybeans. Thus, in the short-run dynamics, the price dynamics of these commodities is affected by common shocks to these markets in addition to dynamics in the futures commodity markets. This is predicted by the storage commodity theory which states that changes in the stock-to-use ratio of these commodities determine the scarcity and consequently the supply and demand equilibrium in the short run. Thus, it is important to considering modelling approaches that provide a more structural approach to the one suggested here in order to capture these price dynamics. Furthermore, and equally important, it is of great interest to understand the extent to which the financialization of commodity markets and the increasing activity of investors in the commodity futures indices are responsible for the seemingly strong price volatility correlation that we observe in our model.

3.7 Conclusion and Policy Implications

In this chapter I have analyzed the degree of interdependence between a number of world agricultural commodities with crude the oil market and three global macroeconomic factors. Our aim has been to establish the level at which volatility in the energy market and instability of global macroeconomic factors are related to these agricultural commodity markets. The relevance of this study arises from two main reasons. The current body of literature emerged as a consequence of the recent commodity price shock, which has strongly argued for the strengthening relationship between energy and commodity markets. In addition it contributes in understanding the channels through which global food prices are affected and often suggests for an adequate policy responses. For this, we have used a VAR-cDCC-MGARCH model to determine the degree of interdependence among these markets from 1982 to 2012 and analyze the stability of this relationship across the sample period.

Our results indicate that although the long-run relationship between global crude oil and agricultural commodity price levels is overwhelmingly strong as shown in the previous chapter, the volatility interdependence between these cannot be explained by the crude oil price returns and macroeconomic factors. For instance, we are not able to establish any interdependence between maize price returns with crude oil prices and macroeconomic factors. Moreover, although soybeans price return presents a negative and statistically significant relationship with the U.S. exchange rate return, it is a weak relationship. Additionally, these results indicate that this relationship is not constant over time and there is evidence of asymmetry during these periods of macroeconomic instability. Similarly, sugar price returns do not present any evidence of being linked with crude oil price returns and any of the macroeconomic factors except the Kilian index of global economic activity. Thus, we can safely conclude that the observed price instability leading to the commodity price shock of 2006-08 is not associated with volatility in the energy or demand-side factors. Thus, our results indicate that in these global agricultural markets the volatility appears to be associated with the financialization of commodities. Our results are in disagreement with those found by Manera et al. [2013] and in line with a number of studies already in the literature such as Gilbert [2010], Irwin and Sanders [2011], Du et al. [2011], Hailu and Weersink [2011], Tang and Xiong [2012a], Pen and Sevi [2013],Ajuzie [2013],Williams [2014], Gilbert and Pfuderer [2014] , Gilbert [2015]. Consequently, from a policy perspective, our results indicate that in order to reduce future agricultural market volatility it is important to create and foment efficient market monitoring mechanisms.

On the other hand, the results from the cDCC model show that crude oil price returns are closely linked with fluctuations in monetary and global macroeconomic policy. Specifically, we determined that crude oil price returns are associated with the U.S. exchange rate and the Kilian index to a lessen extent and present a strong volatility correlation with the rate of U.S. three month treasury bills. These results also confirm the findings of a number of recent studies. For example, Schryder and Peersman [2013] show that changes in the U.S. dollar exchange rate are an important determinant of the volatility of the global price of crude oil given its influence on oil demand. This is because since all commodities are priced in U.S. dollars and consequently it acts as the primary channel through which monetary shocks are propagated through the market. Also, Fattouh et al. [2013] and Knittel and Pindyck [2013] show that economic fundamentals have been the main drivers of volatility in the global oil markets. Similarly, our results also show the importance of monetary policy (interest rates) in determining fluctuations in the global oil market, which also coincides with the findings of Frankel [2008]. More precisely, as interest rates increase, crude oil becomes less attractive as an asset for investors in addition to the fact that contractionary monetary policy has as a main aim to decrease overall demand and that of crude oil. Similarly, positive shocks in the global oil market force central banks to increase interests rate in order to counteract inflationary pressures and thus contribute to a decline in economic activity.

Although the volatility in global agricultural commodity prices has been argued to be linked to a strengthening relationship with energy markets, our results do not support this argument. Moreover, it does not support the view that global macroeconomic factors can explain this phenomena. Consequently, we conclude that there appears to be an excessive volatility in these agricultural commodity markets that cannot be explained by the traditional channels of demand and supply, which makes decisions from a producing and investment aspect very difficult in the near future.

On the other hand, fluctuations in the global crude oil prices are fundamentally explained by global macroeconomic factors and in line with recent developments in the literature. Moreover, we show that the there exists a strong and significant relation between the returns to the futures commodity price index and all the commodities analyzed including crude oil. These results, support the view that a substantial source of the volatility in agricultural commodities, not captured by our model, might be due to the financialization of these commodities. In fact we show that there is strong and significant conditional correlation between the return on commodity index investment and the commodity markets here analyzed. However, as far as to claim that there exists a causal link is beyond the scope our methodology and ultimately an empirical question to address. Therefore, given the results we have presented, a natural extension of our work is to determine the extent to which the financialization of these agricultural commodities is responsible for the observed volatility in these markets.

CHAPTER 4

COMMON FACTORS IN AGRICULTURAL COMMODITY AND ENERGY FUTURES RETURNS: AN ASSET PRICING MODEL WITH REDUCED RANK REGRESSION

4.1 Introduction

In the last fifteen years we have witnessed significant developments in commodity markets. In the early years of the century we saw the spot price of energy and agricultural commodities reaching unprecedented levels. As a consequence, the public and policy makers blamed the 2006/2008 commodity price surge on the increasing financialization of futures commodity markets which enabled them to influence the spot price commodity markets. The concept of "financialization" alludes to the significant rise of financial agents on energy and food futures markets. These claims gained momentum from the fact that by 2008 the oil market had become the world's biggest commodity market and had been transformed by investors from a primarily physical product activity into a sophisticated financial market with a number of participants ranging from oil producers, crude oil physical traders, and refining and oil companies, hedging oil price risk [Chang et al., 2011]. Therefore, the public and a number of politicians claimed that the increase in commodity spot price and volatility was a direct consequence of the financialization of commodity markets which allowed speculative behavior to dominate spot prices. Consequently, it is of the utmost importance to undertake empirical research on these topics in an effort to understand the implications of commodity futures price indexes on energy and commodity spot price and volatility.

In support of the speculative hypothesis, there are the testimonies of a number of key players in the commodities futures markets. For example, in the U.S. Senate testimony, hedge fund manager Michael Masters explained that "...if supply [of commodities] is adequate ...and prices are still rising, then demand must be increasing. What we are experiencing is a demand shock coming from a new category of participant in the commodities futures markets: Institutional Investors. Index Speculators, allocate a portion of their portfolios to 'investments' in the commodities futures market, and behave very differently from the traditional speculators that have always existed in this marketplace." [Master, 2008]. Nevertheless, the current body of literature provides substantial evidence that index investors have had a negligible impact on commodity futures prices [Fattouh et al., 2013, Irwin and Sanders, 2011, 2012a,b, Sanders and Irwin, 2011, 2014]. On the other hand, there is an equal number of authors providing supporting claims in favour of the speculative behaviour and its effect on commodity spot prices [Du et al., 2011, Gilbert and Pfuderer, 2014, Gutierrez, 2013, Hache and Lantz, 2013, Mensi et al., 2013].

In general, futures contracts are agreements between two parties to acquire a certain quantity of a commodity at an agreed price, date and location in the future. Futures contracts are financial instruments designed to minimize one party's exposure to undesirable risk. The futures market is a hybrid marketplace containing two different market participants. One side of the market contains by 'hedgers' who access the market in an effort to reduce their exposure to commodity price fluctuations from their underlying physical commodity activities. On the other hand, the market also contains 'Speculators' who trade in the markets to make maximum profits by buying low and with the expectations of selling high. Thus, on the one hand we have a set of actors who desire to minimize risk (i.e. hedgers), while speculators want to maximize profits and do so by increasing their risk positions.

In this chapter I provide insights into the common risk factors priced in agricultural and energy commodity markets, but more importantly, we aim to estimate their relationship with equities, the U.S. dollar, interest rates, a series variables measuring the global macroeconomic performance (or business cycles) and commodity futures price indexes. Considering that commodity markets often display cross-sectional dependency, we can estimate and subsequently identify risk factors common to a given portfolio of commodities. These results can offer a deep understanding of the risks associated with commodity portfolio investment. I will use the arbitrage pricing theory (APT) to empirically estimate and identify the risk factors associated with the expected return of a well diversified commodity portfolio. Moreover, we are particularly interested in identifying the factor risk premia (factor loadings) of each individual estimated factor, which will tell us the effects of increasing the risk associated with each individual factor to the return of commodity portfolio.

The current body of literature has been limited in searching common components for commodity markets. Particularly it has concentrated its efforts on the pricing of single commodity assets using the Capital Asset Pricing Model (CAPM) and the Consumption Capital Asset Pricing Model (CCAPM). Nevertheless, and for reasons that will be argued in the next sections, commodities are an alternative asset class to equities (for example) and these models pose a number of limitations in explaining the variance and covariance in commodity returns. Moreover, even when alternatives approaches have been applied in order to estimate the common factors in cross-section commodity returns, the literature is limited to estimating the factors based on Principal Component Analysis (PCA) which explanatory power relies on those factors that provide the largest variance in the returns portfolio. However, the estimation of common factors using PCA methodology is limited to explaining the return variances rather than factors that contribute to the explanation of commodity returns. For this reason, we use the APT to estimate the factors and identify the risk associated with fluctuations in equities, the U.S. dollar, interest rates, global demand and commodity futures price indexes on commodity returns. Consequently, by using the APT model we begin our analysis by reviewing the properties of the covariance matrix of the commodity returns and find portfolios that characterize common movement [Cochrane, 2005]. To the best of my knowledge, this is the first time such study has been attempted.

This study contributes to the existing literature by determining common risk components of a portfolio of energy and agricultural commodity price returns. Specifically, I argue that physical commodities belong to an asset class itself and consequently its analysis cannot be treated as capital assets. In this context, I investigate the extent to which traditional, financial and macroeconomic risk factors explain the cross-sectional variation in commodity spot price returns. The aim is to determine if economic fundamentals and financial market (or both) instruments affect the fluctuations in commodity asset returns. Then, I want to establish the extent to which these risk factors are associated with higher fluctuations in our commodity portfolio. For this I use the APT to empirically estimate the risk factors associated with our asset portfolio. The asset portfolio in this case, consists of monthly data for a large number of globally traded commodity prices and crude oil and the macroeconomic and market risk factors with include a series of macroeconomic indicators as well as financial market measures and the Goldman Sachs Commodity Index (S&P GSCI).

4.2 Literature Review

Within the past decade, numerous studies have investigated the role that the financialization of commodities has had on energy and agricultural commodities prices and volatility. In particular, the literature has been very prolific in understanding the implications of the financialization of commodities and its development into an asset class in itself. Nevertheless, very few of these studies have attempted to address the very specific challenges to determine the commodity prices risk components.

Since the 2006/08 commodity price boom economists and policy makers have paid close attention to the role financial investors have in commodity price formation. These investors regard commodity futures as an asset class similar to equities, bonds, real estate and emerging market assets [Gilbert, 2008]. Nevertheless, in a portfolio context, academics and practitioners alike consider commodities as an asset class of their own. That is, commodities present a homogenous risk-return profile (i.e. a high internal correlation) which are due to commodity specific shocks, and a heterogenous risk return profile (i.e. low external correlation) with respect to other asset classes [Fabozzi et al., 2008]. Physical commodities such as energy, grains or livestock, belong to the asset class of consumable or transferable assets[1] [Greer, 1997]. Physical commodities, in contrast with stocks and bonds, do not generate a continuous cash flow, but offer an economic value. For example, crude oil (or energy) is used as an input in the production of virtually all goods in the market. This particular characteristic of physical commodities is what makes them a unique asset class in itself.

For this reason, is not a surprise that 'Capital Asset Price Model' (CAPM) cannot appropriately explain the behaviour of commodity price returns. The traditional CAPM framework considers two types of risk components: (1) systematic (market); (2) unsystematic (asset-specific). The framework further assumes that in a well specified portfolio the unsystematic risk is negligible and it is only the common risk to all assets in the portfolio that matters in the risk profile. The risk premium is then the product of the systematic risk (betas) and the market price of risk, which is defined as the difference between the expected return of the market portfolio and a risk-free asset. In other words, in the CAPM framework, the market 'beta' drives the capital asset price returns. On the other hand, commodity prices depend on global supply and demand factors and not on the market valuation of risk premium as it is the case in traditional asset class. In that sense, we cannot use the CAPM framework and its assumptions in order to explain commodity price returns.

[1] As supposed to capital assets (e.g. stocks) and store of value assets (e.g. real state).

Moreover, the financialization of commodities has added another area of complexity in the analysis of commodity price returns. In the market, investors place their investment positions on commodity futures indices based on the return properties of the set of commodities contained on these futures indices in relation to traditional asset classes [Gilbert, 2008]. Nevertheless, the current body of literature is inconclusive regarding the effects of the financialization of commodity markets on spot price and volatility. There is a limited number of studies that have tried to incorporate the effects of macroeconomic and monetary policy factors together with investment market indicators in order to understand commodity price formations. Consequently, the primary goal of this research is to apply our knowledge of asset pricing theory to developing a statistical model which can explain the cross-section of a portfolio of commodity price returns (i.e. assets) by estimating a set of common factors based on macroeconomic and monetary policy and equity market indicators as well as commodity futures price indices.

There is substantial evidence in the literature of the effects on macroeconomic determinants on commodity returns. In particular, there is extensive discussions on the inflation hedging properties of commodities and their development during business cycles. With respect to the relationship between global business cycles and commodity returns, this is determined by the current state of the economy. This is the case since the demand for commodities is at its highest at the peak of economic activity. Therefore, the current and expected state of macroeconomic variables such as interest rates, inflation and industrial production have an effect on the economic fundamentals of demand and supply of current and expected commodity markets. Consequently, commodity prices are positively correlated with business cycles and we should expect prices to be the lowest during low levels of economic activity and at its hight at peak levels of economic activity [Adams et al., 2008].

The relationship between inflation and commodity returns is defined by the inflation-hedging properties of commodity prices [Greer, 1978]. Commodity futures prices increase when expected inflation increases since commodity futures represent the spot price in the future. In contrast, nominally denominated assets (e.g. bonds, stocks, etc) decrease as inflation and unexpected inflation increases [Adams et al., 2008]. A recent empirical study, Zaremba [2015], showed that commodity futures returns are positively correlated with changes in inflation (mainly the U.S. CPI) and thus have retained inflation hedging properties and particularly over the recent years. Given these properties, we have seen a significant development of the use of commodity futures indices as financial instruments within the past fifteen years and links between them and speculative behaviour in commodity markets.

The empirical literature has recently produced a number of studies in an effort to understand the relationship between the financialization of commodities and futures index investments. For example, Tang and Xiong [2012a] found that non-energy futures have become increasingly correlated with oil prices during the same period in which we saw index investment in commodity markets reach unprecedented levels. Also, recent studies have also concluded that prices for individual commodities cannot be solely determined by supply and demand factors, but also by the risk appetite for financial assets and the investment behaviour of diversified commodity index investors [Kaufmann and Ullman, 2009, Tang and Xiong, 2012b]. Similarly, Tokis [2011] provides evidence that investors with hedging positions in crude oil markets can destabilize the interaction among commercial participants and liquidity-providing speculators. More recently, Basak and Pavlova [2015b] also concludes that there exists a comovement between commodity prices and volatilities and the presence of institutional investors in futures markets. On the other hand, Czech [2013] concludes that from January 2006 to December 2012 index traders' net positions in maize and wheat markets might have had an effect on futures price movements in these markets.

Despite the evidence provided in these studies, there is a significant number of papers that conclude that there is no effect of financial speculation on commodity prices or returns. Using a number of different approaches, Alquist and Coibion [2013], Brunetti et al. [2013], Büyükşahin and Harris [2011], Kilian and Murphy [2014] find very little evidence of speculative behaviour caused by investors in commodity markets. For instance, in a recent study, Hamilton and Wu [2015] find no evidence that index-fund investing has an effect on commodity futures prices. Also, Büyükşahin and Robe [2014] use a non-public dataset of trader positions in 17 U.S. commodity futures markets to provide evidence of no relationship between the rates of return in these commodity futures indices and the investment positions of commodity swap dealers and index traders.

There are two studies that present similar underlying assumptions to the one here proposed. The first study being that by Daskalaki et al. [2014] and also by Chavallier and Ielpo [2013], which is an extension of an early verision of Daskalaki et al. [2014]. Daskalaki et al. [2014] studied the common components of a number of commodity futures using a number of APT models and PCA. Here, Daskalaki et al. implemented a series of models rather suited for equity analysis such as CAPM and CCAPM (and variations of these) in order to account for several factors such as real money growth (Money-CAPM and Money-CCAPM) in order to account for commodities' influence by monetary policy as suggested by Anzuini et al. [2012], Scrimgeour [2015]. In term of the macro-shocks models (e.g. CAPM, CCAPM, MCAPM and MCCAPM), the authors find that the industrial production growth shocks, consumption growth shocks, inflation shocks, interest rate shocks and GDP growth shocks do not price the cross section of commodity futures returns. Additionally, the authors follow [Erb and Harvey, 2006] arguments and use an international-CAPM model to evaluate the premise of commodity futures being affected by exchange rate risk. In summary, the authors are unable to explain any cross-section of the commodity futures using any of the macro, equity-motivated, or commodity-related factors prices. Instead, Daskalaki et al. take an alternative approach and turn to explain the cross-section of commodity futures using commodity specific factors. However, commodity specific factors are also unsuccessful in pricing commodity futures. Alternately, Daskalaki et al. implement five different versions of a PCA factor model using both monthly and quarterly data. Yet again, the authors conclude that the PCA models performs poorly. Therefore, the authors conclude by arguing that a possible explanation is the heterogenous structure of commodity futures markets.

There exist a number of advantages and equally number of limitations from implementing a PCA. The main advantage is that in this case, the authors do not have to construct the candidate factors a priori and thus rely on the data to determine the candidate factors[2]. However, in the case of Daskalaki et al., the performance of the PCA is heavily influenced by the frequency of the data used (e.g. monthly, quaterly). Also, the nature of PCA is to capture the variance and consequently is only able to only account common variation in commodity returns. Additionally, the factors derived from the PCA cannot be attributed

[2]In this case, the authors use a two step Fama-MacBeth [Fama and MacBeth, 1973] regression to determine their respective risk premiums.

to a specific individual or group of commodities, thus it is not very informative if one is interested in the specific factors that contribute to the explanation of commodity returns.

To this extent, Chavallier and Ielpo [2013] expanded the work of Daskalaki et al. [2014] by using a criteria to determine the number of factors to include in the PCA rather than to include all factors. This approach allows to identify the factors (through a correlation analysis) and then analyze their dynamic properties over time. In this approach, Chavallier and Ielpo [2013] estimate the number of factors to include in the PCA is decided using the criteria proposed by Alessi et al. [2010] and is a refinement of that by Bai and Ng [2008]. When Chavallier and Ielpo [2013] apply their identification strategy, the authors find that variances in commodity markets are significantly due to commodity specific (idiosyncratic) variations in commodities, which cannot be captures by common factors. Thus, Chavallier and Ielpo decide to include three factors for equities market, two for interest rates and finally one for the exchange rate market. Using this approach, the authors conclude that the explanatory power of the variance in commodity futures returns only explains about 28% of the total variance in the commodity dataset. This conclusion emphasizes the findings in the literature that if investors are able to diversify their commodity portfolio, idiosyncratic shocks present no risk to their portfolio return. Conversely, it is the common components and thus the correlation between these factors (and their components) and commodity returns that is important to be able to explain commodity returns.

To the best of our knowledge there is no study yet, which has focused on the factors that contribute to explaining commodity returns. Thus far, the literature has been limited to studies that have focused on the commodity-specific effects less so on common factors. Instead, we are interested in identifying a a set of systematic factors which may price the common variation of a portfolio of commodity returns. Particularly, we want to identify if any macroeconomic factors and in particular monetary policy and exchange rates constitute systematic determinants of prices for the cross-section of these commodities. Additionally, we are interested in determining any factor that is associated with commodity investment and their ability to hedge against inflation. The extent to which commodity returns are increasingly related to common factors, is an important feature for all commodity market participants in spot and equal those that use futures to hedge commercial positions.

4.3 Methodology

The arbitrage pricing theory (APT) was characterized on a statistical basis by Ross [1976]. The core idea is that there exists common components to the return on stocks. In other words, positive shocks in the market are expected to have the same positive effect on individual stocks. Moreover, individual stock's return has a completely idiosyncratic dynamic (i.e. asset specific realized return). Therefore, by holding portfolios, investors can diversify away from individual returns, which in turn implies that the completely idiosyncratic dynamics in asset returns (or prices) should not contain any risk prices. Consequently, expected returns on an asset should be related to the asset's covariance with only the common components ("factors") [Cochrane, 2005]. The central motivation of our research lies in the foundation of these concepts.

Generally, fluctuations in food commodity markets are attributed to the forces of demand and supply. In the short run, individual commodity supply shocks ("asset specific") are argued to be dominant in causing price fluctuations with demand shocks having a lesser impact [Gilbert, 2010]. Nevertheless, across crops supply shocks will be weakly correlated whereas in contrast demand factors may have a much larger role in the volatility of prices. Therefore, one can argue that demand components are the main determinants of commodity price movements at the aggregate level with idiosyncratic supply components having a negligible impact on the commodity price returns. The APT captures the behavior of these commodity return co-movements via a statistical factor decomposition [Cochrane, 2005]. Essentially, this is the intuition captured by the APT presented above and the reason we have chosen to apply this methodology to our research question.

One of the important implications underlying the CAPM model is that the market portfolio plays a role representing a risk factor from which the equilibrium price is derived. In this sense, the APT is a generalization of the CAPM model in that it considers a model for returns Y_t (either both net or excess returns) and one or more risk factors f_t, which can also be observable or not observable[3]. Moreover, the APT is argued to be more appropriate than the CAPM not just because it generalizes the concepts behind the CAPM itself, but because it requires no utility assumption and is based on a linear return generating process as its core assumption [Roll and Ross, 1980].

Consider N asset returns, $Y_t \epsilon \mathbb{R}^N$, and $k < N$ risk factors, $f_t \epsilon \mathbb{R}^k$. The APT model considers a model for $(Y_t, f_t)_{t=1,2,\ldots,T}$ by proving the conditional equation of Y_t conditional on f_t, the past information set, $\mathcal{F}_{t-1}$, and a chosen marginal equation for f_t. Thus, the asset returns can be expressed by a linear factor model,

[3] In this case, we are only interested in observable risk factors only, but equally one can use not observable factors.

which in this case represents both the APT and CAPM (restricted to $k = 1$), where the conditional model for Y_t conditional on f_t is as follows:

$$Y_t = \mu + \mathbf{B}f_t + \varepsilon_t, \tag{4.1}$$

where $\mathbf{B}$ are the *factor loadings*, ε_t are the residuals and are assumed to be *iid* $N_N(0, \Sigma)$, with $\Sigma > 0$, and $\mathbb{E}_{t-1}(f_t) = 0$ such that $\mathbb{E}_{t-1}(Y_t) = \mu$ and $\mathbb{E}_{t-1}(Y_t|f_t) = \mu + \mathbf{B}f_t$[4]. Also, f_t denotes the vector of 1 through k risk factors such that $f_t = [f_1, f_2, \ldots, f_k]$. For example the CAPM model with constant β loadings is equivalent to Equation 4.1 by setting $k = 1$, $Y_t = r_t = (R_{1,t} - R_f, \ldots, R_{N,t} - R_f)'$ and $f_t = r_{m,t} - \mathbb{E}_{t-1}(r_{m,t})$ such that $\mathbb{E}_{t-1}(f_t) = 0$. Note that in this specification $\mathbb{E}_{t-1}(r_t) = \mu$ while the CAPM states that $\mathbb{E}_{t-1}(r_t = \beta\mathbb{E}_{t-1}(r_{m,t})$, which implies that the CAPM is a special case of the APT such that $\mathbf{B} = \beta$ and,

$$\mu = \beta\lambda_1$$

where $\lambda_1 = \mathbb{E}_{t-1}(r_{m,t})$ and is assumed to be constant, this represents the expected excess return on the market portfolio.

4.3.1 Estimation and Testing of the Observable Factor Models

One of the implications that arise from Equation 4.1 when the factors,f_t, are observable is that they are assumed to be exogenous. For example, as observable factors one might consider contemporaneous macro-variables, lagged returns or market specific indicators. However, these factors most fulfil the condition shown

[4]It is worth noting that Equation 4.1 assumes constnat $\mathbf{B}$ and μ, but there is no reason to reformulate this equation such that $\mathbf{B}$ and μ are time-varying.

in Equation 4.1 where $\mathbb{E}_{t-1}(f_t) = 0$, which needs a join specification for (Y_t, f_t).

The simplest case is where (Y_t, X_t) are assumed to be *iid* $N_{N+k}(\theta, \Omega)$, where X_t, with $\theta \in \mathbb{R}^{N+k}$ and $\Omega \in \mathbb{S}^{N+k}$,where $\mathbb{S}$ denotes the space of positive definite matrices and X_t is a set of candidate factors to be considered. Lets denote $\theta = (\theta_y', \theta_x')'$ and

$$\Omega = \begin{pmatrix} \Omega_{yy} & \Omega_{yx} \\ \Omega_{xy} & \Omega_{xx} \end{pmatrix} \tag{4.2}$$

we can rewrite Equation 4.2 as,

$$Y_t = \theta_y + \varepsilon_{yt} \tag{4.3}$$

$$X_t = \theta_x + \varepsilon_{xt} \tag{4.4}$$

where $\varepsilon_t = (\varepsilon_{yt}', \varepsilon_{xt}')'$ is *iid* $N_{N+k}(\theta, \Omega)$. Therefore, by the properties of the Gaussian distribution, the conditional model for Y_t given X_t is provided by,

$$Y_t = \theta_y + \beta(X_t - \theta_x) + \varepsilon_t \tag{4.5}$$

where $\beta = \Omega_{yx}\Omega_{xx}^{-1}$, ε_t is *iid* $N_{N+k}(0, \Omega_{yy \cdot x})$ and $\Omega_{yy \cdot x} = \Omega_{yy} - \beta\Omega_{xy}$. Consequently, we can redefine $f_t = (X_t - \theta_x)$, $\mu = \theta_y$ and $\Sigma = \Omega_{yy \cdot x}$ from Equation 4.1. In summary, the risk factors, f_t, are now defined as the excess return on X_t corrected for its mean.

The estimation procedure for the unrestricted parameters, and in particular θ_y, can be performed either in the simultaneous model from Equations 4.3-4.4 or by using the conditional model as in Equation 4.5 and the marginal model from

Equation 4.4 separately. The latter approach is the modelling choice we pursue in our study.

The conditional model can be described as follows,

$$Y_t = \beta(X_t - \theta_x - \lambda) + \varepsilon_t \tag{4.6}$$

where I evaluate the joint likelihood function for $Z_t = (Y_t', X_t')'$ by maximum-likelihood estimation (MLE). More specifically, we first estimate $\hat{f}_t = X_t - \hat{\theta}_x$ by regressing X_t on a constant. Then, we estimate $\hat{\beta}$, $\hat{\theta}_y$ and $\hat{\lambda}$ under the no-arbitrage condition ($\theta_y = \beta\lambda$)[5] by OLS of Y_t on $\hat{f}_t$ and a constant. Thus, we replace f_t by the estimated $\hat{f}_t$. However, this approach presents significant challenges from a modelling point of view since even in its simplest form it does not lead to the MLE. Therefore, in the case where we want to test whether we have one or more risk factors (CAPM vs. APT) by using the likelihood ratio (LR) test statistic in a two-step estimation, we might not be able to provide conclusive evidence. In conclusion, we need to specify a joint model for Y_t and the candidate factors X_t before we proceed to estimate and test the specifications.

In addition to the model presented in Equation 4.1 we can include dynamic factors into the equation. For example, holding the same assumptions as above, in the case of a vector-autoregressive model of order one, VAR(1), we can rewrite the candidate factors as,

$$X_t = \theta_x + \phi X_{t-1} + \varepsilon_{xt} \tag{4.7}$$

[5]The no-arbitrage condition for the general APT states that the expected excess returns $\mu = \mathbb{E}_{t-1}(Y_t) \in \mathbb{R}^N$ are spanned by k risk factors.

where Y_t is given by Equation 4.5 (as before), and the conditional model for Y_t given X_t and the set of past information, $\mathcal{F}_{t-1}$, $X_{t-1}, \ldots, X_0$ and $Y_{t-1}, \ldots, Y_0$, is provided by,

$$Y_t = \theta_y + \beta(X_t - X_{t-1} - \theta_x) + \varepsilon_t \tag{4.8}$$

where as before we estimate f_t as $f_t = X_t - \phi X_{t-1} + \theta_x$ and as before, we use the same assumption and no-arbitrage condition. Likewise, to obtain the MLE we need to estimate $\hat{f}_t = X_t - \hat{\phi} X_{t-1} - \hat{\theta}_x$, where the two-steps rely on the estimation of X_t on a constant and its past values.

4.3.2 Number of Factors and Reduced Rank Regression (RRR)

As we have previously argued, Equation 4.1 presents significant challenges from a statistical and modelling approach. Although, we might be able to derive it in its most simple form by assuming an *iid* joint model, this regression is not equivalent to MLE when setting the restrictions for CAPM and APT. Therefore, in order to implement these restrictions we first must provide a specification for the joint model for Y_t and the known X_t or f_t (the candidate factors). Here, I will discuss an approach in which likelihood-based estimation can be used in determining the number of factors of the APT model.

As before, lets consider N return assets, $Y_t \epsilon \mathbb{R}^N$, given by

$$Y_t = \Pi Z_t + \varepsilon_t \tag{4.9}$$

where ε_t are assumer to be *iid* $N_N(0, \Omega)$ and $\mathbb{E}_{t-1}(Y_t|Z_t) = \Pi Z_t$, with Π is a general $N \times p$ dimensional matrix, for $N \geq p$, and $Z_t \epsilon \mathbb{R}^p$. We can include a constant, μ, which may not satisfy $\mathbb{E}_{t-1}(Z_t) = 0$ and identify the factors, Z_t, in terms of the f_t as a reduced rank regression (RRR). That is, if all factors, p, are important then Π will have full column rank and $p = k$ and $\Pi = \mathbf{B}$. However, if the rank of Π is less than the number of factors, that is $r < p$, then Π has reduced rank and we can define,

$$\Pi = \alpha\gamma' \tag{4.10}$$

where α and γ have $N \times r$ and $p \times r$ dimensions respectively. Thus, from Equation 4.10, α is equivalent to $\mathbf{B}$ in Equation 4.1, $\alpha = \mathbf{B}$, and we have $r = k < p$ number of linear combinations and $\gamma' Z_t$ would be the estimated number of important factors in the estimation. Consequently, by using RRR we can determine the number of linear combinations or common factors. Furthermore, we can use a log-likelihood ratio test (LR) in order to determine the number of linear combinations by maximizing the likelihood function under the null hypothesis ($\mathcal{H}_r$) of reduced rank of Π (rank(Π) $\leq r$) against the alternative ($\mathcal{H}_p$) of rank(Π) $\leq p$ [Johansen, 1996, Velu and Reinsel, 1998].

Estimation of the Reduce Rank Regression

As in the previous section, under the null hypothesis ($\mathcal{H}_r$), we know that Π has reduced rank and thus we can use MLE to test the number of linear combinations. Under $\mathcal{H}_r$ the RRR($Y_t|Z_t$) model is given by

$$Y_t = \alpha\gamma' Z_t + \varepsilon_t,\ t = 1, \ldots, T \tag{4.11}$$

where α and γ have $N \times r$ and $p \times r$ dimensions respectively. The algorithm we have implemented in order to estimate the RRR has been obtained primarily from Reinsel and Velu [1998] and built upon lecture notes from Johansen [2007]. The log-likelihood function is given by,

$$log\ L(\alpha,\gamma,\Omega) = -\frac{T}{2}log|\Omega| - \frac{1}{2}\left(\Omega^{-1}\sum_{t=1}^{T}(Y_t-\alpha\gamma' Z_t)(Y_t\alpha\gamma' Z_t)'\right) \tag{4.12}$$

Moreover, we can estimate $\hat{\alpha}(\gamma)$ and $\hat{\Omega}(\gamma)$ by using OLS of Y_t on $\gamma' Z_t$ by fixing γ,

$$\hat{\alpha}(\gamma) = S_{yz}\gamma(\gamma' S_{zz}\gamma)^{-1}, \text{ and } \hat{\Omega}(\gamma) = S_{yy} - S_{yz}\gamma(\gamma' S_{zz}\gamma)^{-1}\gamma' S_{zy} \tag{4.13}$$

where $S_{zy} = S'_{yz} = \frac{1}{T}\sum\limits_{t=1}^{T} Z_t Y'_t$, $S_{yy} = \frac{1}{T}\sum\limits_{t=1}^{T} Y_t Y'_t$ and $S_{zz} = \frac{1}{T}\sum\limits_{t=1}^{T} Z_t Z'_t$. Thus, replacing these into Equation 4.12, we get the concentrated likelihood function,

$$log\ L_c(\gamma) = log(\alpha(\gamma),\gamma,\Omega(\gamma)) = -\frac{T}{2}log|\hat{\Omega}(\gamma)| - \frac{TN}{2} \tag{4.14}$$

We can represent this in matrix form as follows,

$$\begin{aligned}\left|\begin{pmatrix} S_{yy} & S_{yz}\gamma \\ \gamma' S_{zy} & \gamma' S_{zz}\gamma \end{pmatrix}\right| &= |S_{yy}||\gamma'(S_{zz} - S_{zy}S'_{yy}S_{yz})\gamma| \\ &= |\gamma' S_{zz}\gamma||S_{yy} - S_{yz}\gamma(\gamma' S_{zz}\gamma)^{-1}\gamma' S_{zy}|,\end{aligned}$$

also, from Equation 4.13, it is evident that,

$$\begin{aligned}|\hat{\Omega}(\gamma)| &= |S_{yy} - S_{yz}\gamma(\gamma' S_{zz}\gamma)^{-1}\gamma' S_{zy}| \\ &= |S_{yy}|\frac{|\gamma'(S_{zz} - S_{zy}S_{yy}^{-1}S_{yz})\gamma|}{|\gamma' S_{zz}\gamma|}\end{aligned}$$

thus, we can rewrite Equation 4.14 as,

$$log\ L_c(\gamma) = -\frac{T}{2} log\left(\frac{|\gamma'(S_{zz} - S_{zy}S_{yy}^{-1}S_{yz})\gamma|}{|\gamma' S_{zz}\gamma|}\right) - \frac{T}{2}|S_{yy}| - \frac{TN}{2} \tag{4.15}$$

and we need to minimize the following expression,

$$\frac{|\gamma'(S_{zz} - S_{zy}S_{yy}^{-1}S_{yz})\gamma|}{|\gamma' S_{zz}\gamma|}$$

over γ in order to find the MLE for $\hat{\gamma}$. According to Johansen [1996], this is the same as maximizing by a reduced rank regression and we proceed by solving the following eigenvalue problem,

$$|\lambda S_{zz} - S_{zy}S_{yy}^{-1}S_{yz}| = 0, \tag{4.16}$$

for the eigenvalues $\hat{\lambda}_i$, $\forall i = 1, \ldots, p$, $\hat{\lambda}_1 \geq \hat{\lambda}_2 \geq \cdots \geq \hat{\lambda}_p \geq 0$, with the following eigenvectors, $\hat{v}_i$ such that $\hat{\lambda} = (\hat{v}_1, \ldots, \hat{v}_r)$. Then, we know that r^{th} eigenvector corresponds to the largest r^{th} largest eigenvalue. For this problem the maximum likelihood function is given by,

$$L_{MAX}(\mathcal{H}_r) = L_c(\hat{\gamma}) = \left(|S_{yy}| \prod_{i=1}^{r}\left(1 - \hat{\lambda}_i\right)\right)^{-\frac{T}{2}} \tag{4.17}$$

Also, the eigenvalue problem presented in Equation 4.16 is a generalized eigenvalue problem, where the eigenvectors, $V = (v_1, \ldots, v_p)$ satisfies the following identity, $V' S_{zz} V = \mathbf{I}_p$ in addition to $V' S_{zy} S'_{yy} V = \Lambda = diag(\lambda_1, \ldots, \lambda_p)$.

Determining the number of Factors

As we outlined in previous sections, in order to test for the number of factors we use the likelihood ratio test. In this case, we are interested in testing the null hypothesis of $\mathcal{H}_r$, against the alternative of $\mathcal{H}_p$. This is a trivial procedure and is given by,

$$LR(r|p) = -T \sum_{i=r+1}^{p} log(1 - \hat{\lambda}_i) \simeq T \sum_{i=r+1}^{p} \hat{\lambda}_i, \tag{4.18}$$

from this, we recognize that if the rank of Π is less than the number of factors, $r < p$, then we have reduced rank and the $p - r$ smallest eigenvalues will not be different from zero. Also, under the assumption that the 'Central Limit Theorem' (CLT) and 'Law of Large Numbers' (LLN) applies to Y_t and Z_t, the likelihood ratio statistic follows a χ^2 distribution with $(N - r) \times (p - r)$ degrees of freedom.

In our case we have included a constant, which in turns takes the following form,

$$Y_t = \mu + \Pi Z_t + \varepsilon_t, \tag{4.19}$$

then we can still solve this problem by subtracting the mean from both Y_t and Z_t such that $\tilde{Y}_t = (Y_t - \bar{Y}_t)$ and $\tilde{Z}_t = (Z_t - \bar{Z}_t)$ where we define $\bar{Y}_t = \frac{1}{T} \sum_{t=1}^{T} Y_t$ and $\bar{Z}_t = \frac{1}{T} \sum_{t=1}^{T} Z_t$ respectively, and replace these into S_{yz}, S_{zz} and S_{yy} as described above. Therefore, in this case, and as was previously argued, the joint model of Y_t and the candidate factors X_t refer to the same objective as if we rewrite $f_t = Z_t$, which is the same as the previous candidate factors, but corrected by its mean.

In this approach there is a fundamental difference to that generally found in the existing literature. In this case, we are determining the number of k linear combinations of X_t, which maximizes (minimizes) the correlation with linear combinations of Y_t. This is defined by Johansen [2007] as finding the canonical correlations. Instead, the literature we have observed used instead a principal components approach. In this case, principal component provides ν linear combinations of X_t which minimizes the variance. Consequently, since in our study we are interested in studying the correlations between the asset returns, Y_t and candidate risk factors, $f_t(X_t)$, using the principal components approach appears not to be relevant and would have lead to misleading conclusions.

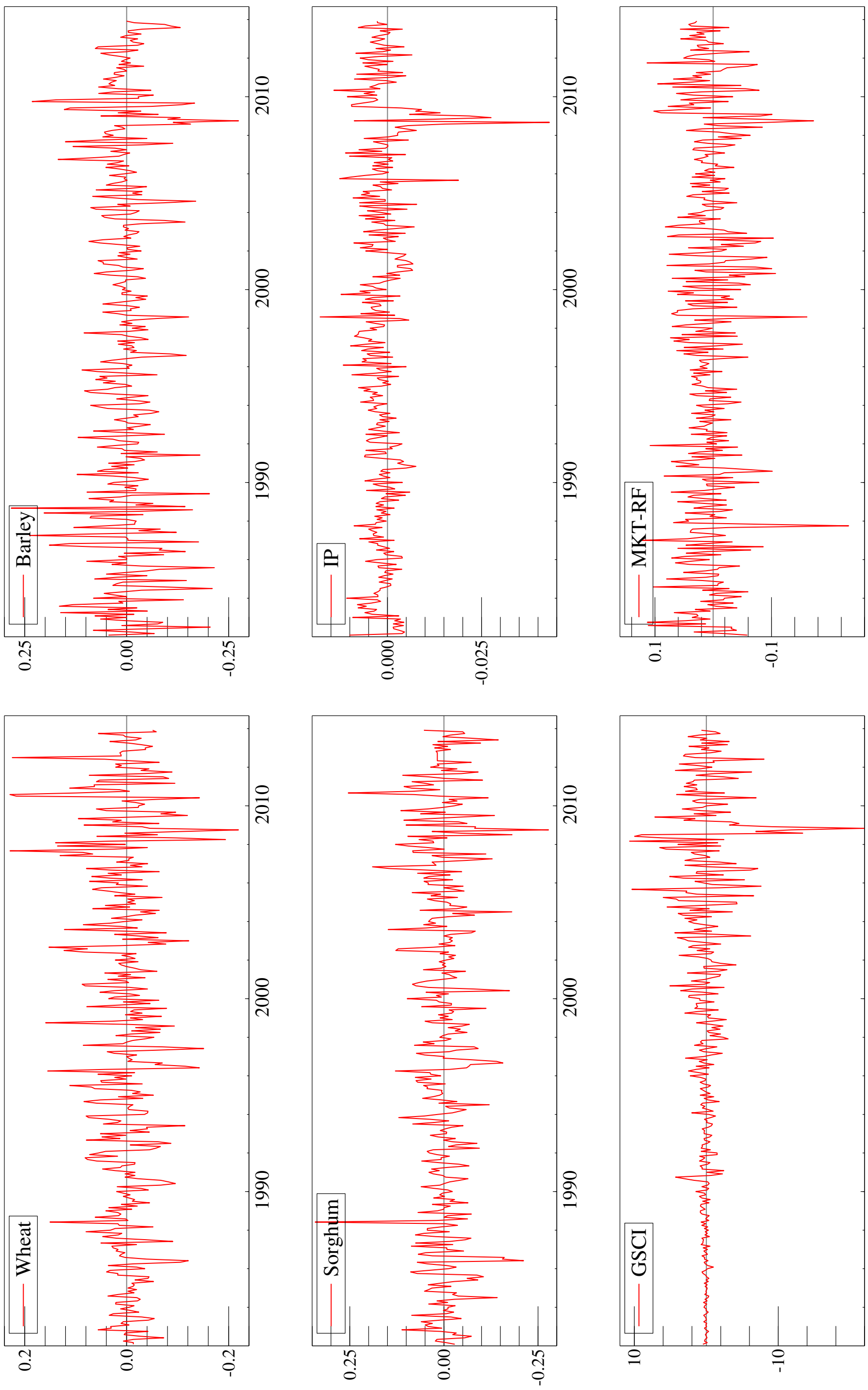
4.4 Empirical Analysis

4.4.1 Data Description

The data used in the analysis consists of six agricultural commodity price series (e.g. maize, soybean, sugar, wheat, barley and sorghum) and crude oil prices and has been obtained from the IMF International Financial Statistics (IFS) library. As before, I use the weighted U.S. dollar exchange rate and three-month Treasury bill secondary market rate as reported by the Board of Governors of the Federal Reserve System, the U.S. Industrial Production and as a measurement of real global economic activity (Y_t) I use Lutz Kilian's index of global real economic activity Kilian [2009]. We further use the Goldman Sachs Commodity Index (S&P GSCI), which represents a long-only investment position in commodity futures. We also use the excess return on the market (Rm-Rf) from Ken French's website. Additionally, we compute simple monthly returns for the commodity and crude oil price series. Our sample spans the period January 1982 to December 2013 for a total of 384 monthly observations.

We are interested in empirically determining the factors that contribute to the time variation in the commodity price risk premia. Primarily we are concerned with the set of factors that are common to the cross section of the commodity portfolio rather than idiosyncratic shocks. Therefore, using these variables we argue that it is possible to capture investors sentiment about the state of the market from the macroeconomic indicators U.S. exchange rate, short-term interest rate, the U.S. Industrial Production and global index for economic activity. On the other hand, we are also interested in determining if investment in futures commodity indices and the excess return on the market has an effect on the risk premia of our commodity portfolio. The use of the S&P GSCI index as a proxy for the commodity market portfolio has been theoretically justified by Daskalaki et al. [2014]. The authors argue that using this futures commodity index as a proxy for the commodity market portfolio is adequate since the sum of all futures contracts net out to zero after all positions (long/short) are added together. Figure 4-1 shows the series that have not been presented in the previous chapters (i.e. wheat, barley, sorghum, industrial production, the GSCI index and the excess return on the market) while Figure 3-2 (from previous chapter) shows the remaining series.

Figure 4-1: *Commodity price returns and market indices.*



4.4.2 Empirical Results and Discussion

In our analysis we assume the number of factors to be unknown. As we indicated in a previous section, we first determine the candidate factors from the macroeconomic variables, GSCI index and the excess return on the market for our portfolio of commodity price returns. For this, we estimate a VAR(3) by minimizing the Schwarz (SC) and Hanna-Quinn (HQ) information criteria and considering the model misspecification of no serial autocorrelation in the error term. Subsequently, we solve a generalized eigenvalue problem and use the likelihood ratio (LR) to test the rank order of the Π matrix. We hope to find a reduced rank, which determines the number of risk factors to our commodity portfolio.

Table 4.1: *The rank analysis for the factor model.*

Rank of Π		
Rank	$LR^{\dagger}$	P-$Value$
$r = 0$	227.382	0.000^{***}
$r \leq 1$	68.839	0.001^{***}
$r \leq 2$	41.669	0.020^{**}
$r \leq 3$	18.965	0.271
$r \leq 4$	8.329	0.501

Notes: Significance at the the 1%, 5% and 10% level are denoted by $^{(***)}$, $^{(**)}$ and $^{(*)}$ respectively. (†) has a χ^2 distribution with $(N-r)(p-r)$ degrees of freedom.

In order to determine the number of unknown factors, we need to test the hypothesis under the null that the Π matrix (as previously defined) has a reduced rank. Table 4.1 shows the likelihood ratio test for up to rank four of the Π matrix with the respective p-values. The test shows that the Π matrix of factors has three linear combinations or equivalently that it has a rank equal to three. This test indicates that we have three factors that can possibly explain common variations in our commodity portfolio. Moreover, we can exactly calculate the percentage of risk premia that each of these factors contributes to our portfolio by constructing a weighted average across all estimated eigenvalues. The eigenvalue with greater weight will present greater risk to that specific factor. Table 4.2 show that the first factor contributes about 66% of the covariance, and the second and third factor significantly less with about 13% and 11% respectively. In total, the three factors explain approximately 90% of the covariance in the commodity portfolio, leaving only the remaining 10% explained by a combinations of factors not included in the analysis.

Table 4.2: *Explanatory power for each factor*

Number of Factors				
	f_1	f_2	f_3	Total
Percentage of factor	0.659%	0.133%	0.112%	0.905%

The next step in our analysis is to identify the components in each of the factors individually. This is possible by setting just identifying restrictions on each individual estimated factor by normalizing through one of the variables of interest. Since these are just identifying restrictions, it does not matter the variable by which one normalizes the factor. However, we have decided to set just identificatying restrictions according to the magnitude and empirical hypothesis we want to describe. In particularly, we are interested in determining the extent to which the futures commodity index and the excess return on the market affect the risk premia in to our commodity portfolio. We suspect that the first factor, given its weight, is related to the macroeconomic activity due to the magnitudes and significance level of the variables associated with these macroeconomic variables in the model. On the other hand, the second and third factors are more difficult to determine since these have very similar weights. However, given the composition of significant coefficients in the composition of the first factor, we suspect that uncertainty in the market should not have a large weight in the covariance of our portfolio, consequently we expect market forces to be reflected in these two factors.

Figure 4-2 shows each of the estimated factors and the sum of all three during the period. The estimation was conducted as explained in the previous sections and where weak convergence of the system was obtained through the BFGS (Broyden-Fletcher-Goldfarb-Shanno) algorithm using Oxmetrics. All factors show levels of low fluctuations at the beginning of the sample with some evidence of short-lived spikes. However, at the beginning of 2000 it is clearly the starting point of major periods of fluctuations relative to those seen in the previous part of the sample. Another important observational characteristic from Figure 4-2 is that factors two and three appear to mimic each other very closely and both appear to have counter cyclical variations relative to the first factor. Nevertheless, the dominant components overall are those associated with the variations of the first factor. Nevertheless, as it stands, one can say very little about the origin of this phenomena or to draw any meaningful conclusions other than explaining how each factor compares to each other. The first factor shows a distinct difference from the second and third. It appears that for each movement in the first factor there is a mirror movement in both the second and third factor. Figure 4-3 shows this evidence very distinctly. Consequently, it appears that the second and third factors are associated with hedging positions (e.g. commodity futures) in the commodity market associated with fluctuations in the first factor (e.g. the macroeconomics or fundamentals). This would be consistent if we can identify the first factor as that associated with the risk premia due to fluctuations in macroeconomic indicators. Therefore, the next step is to identify each individual factor by determining which variables composing each factor is statistically significant.

Figure 4-2: *Individual Estimated Factors 1-3 (1982-2013)*

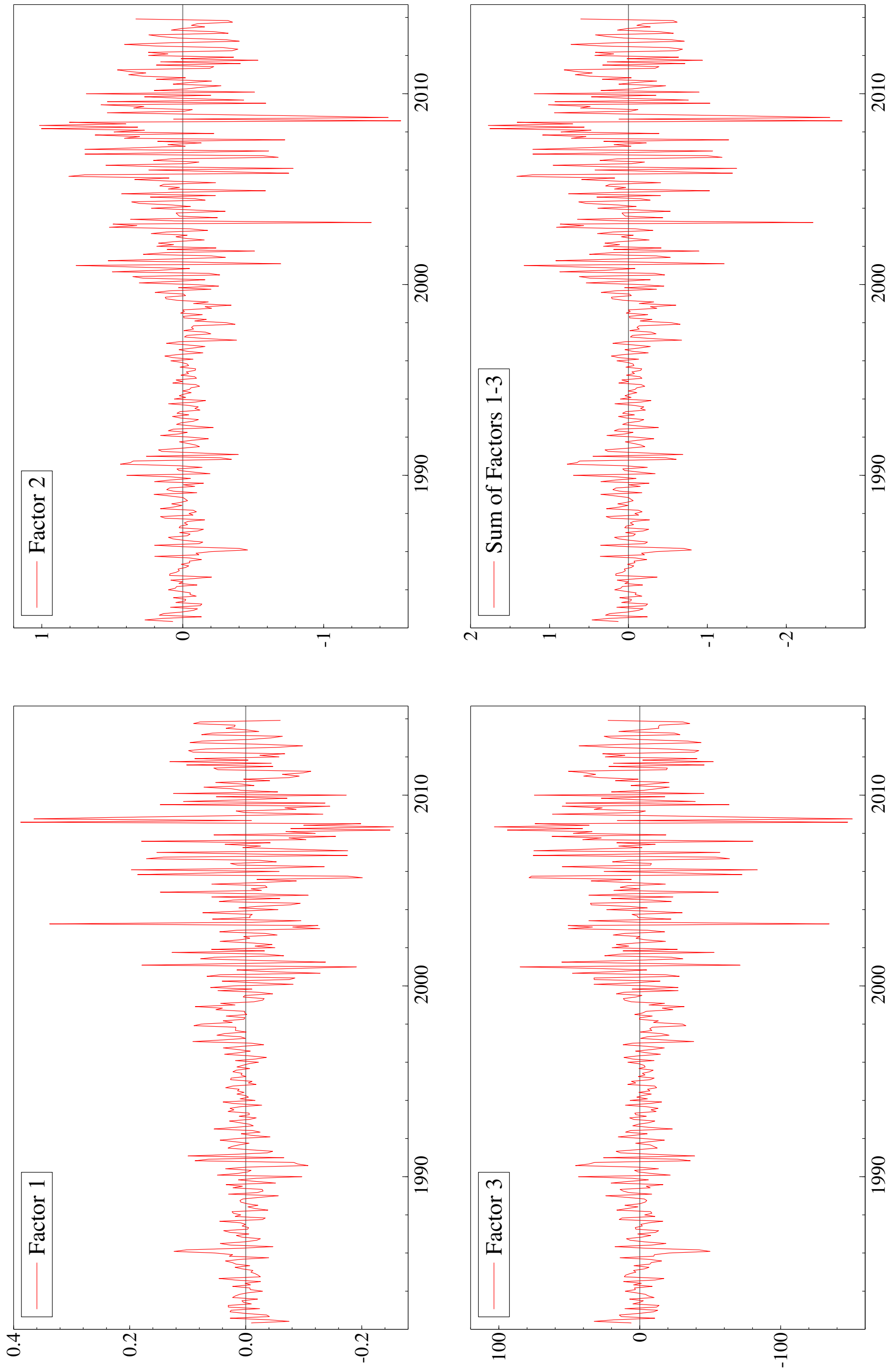
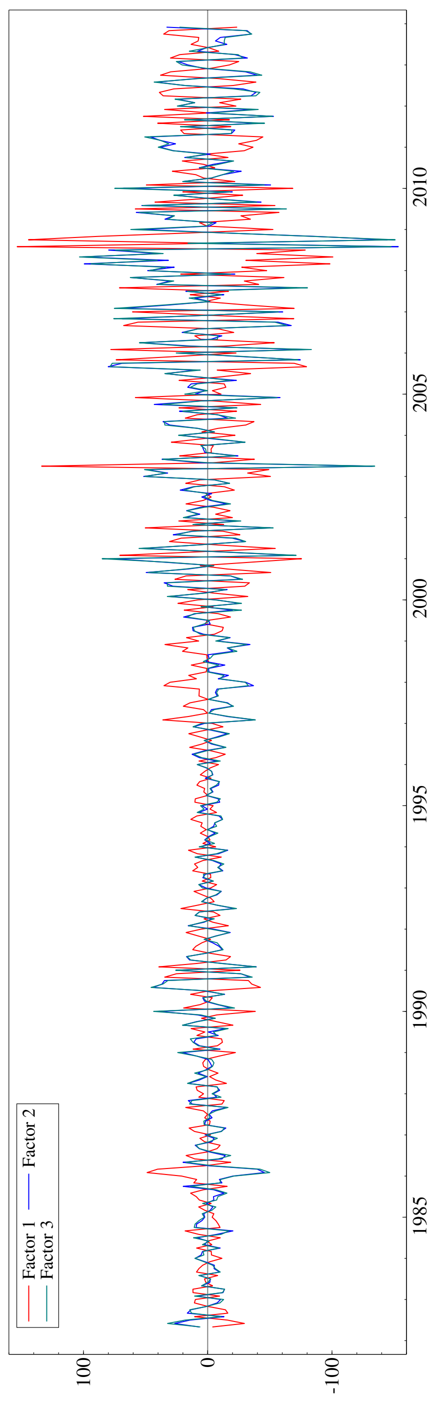


Figure 4-3: *All Estimated Factors 1-3 (1982-2013)*



In order to achieve identification of the factors (and factor loadings), we impose just identifying restrictions on each factor loading (i.e. γ' from Equation 4.10). For example, this can be done by normalizing the first factor by the global economic activity index, the second factor by normalizing it by the short term interest rates and finally the third factor by doing this with the futures commodity price index. All the results are presented in Table 4.3. The results suggest that the first factor is associated with fluctuations in the index for global economic activity and the exchange rate given that these two are the only significant components in the factor loadings. The second factor, is associated with the short-term interest rate and the excess return on the market. Finally, the third factor appears to be capturing the relationship between the future commodity index with inflation and again the excess return on the market[6].

Table 4.3: *Factor Loadings of the* Π *matrix*

Factor Loadings ($\Pi = \alpha\gamma'$)			
	γ_{f_1}	γ_{f_2}	γ_{f_2}
y	1	0	0
i	0	1	0
GSCI	0	0	1
inf	2.818 [0.468]	0.062 [0.024]	110.971^{***} [10.483]
xr	16.968^{***} [3.314]	0.040 [0.012]	-6.227 [-0.459]
ip	16.292 [1.285]	-16.691 [-1.545]	-0.063 [-0.054]
Rm-Rf	0.023 [0.047]	-107.620^{***} [-54.502]	44.703^{***} [5.478]

Notes: Significance at the the 1%, 5% and 10% level are denoted by $^{(***)}$, $^{(**)}$ and $^{(*)}$ respectively. The t-statistics are reported in brackets.

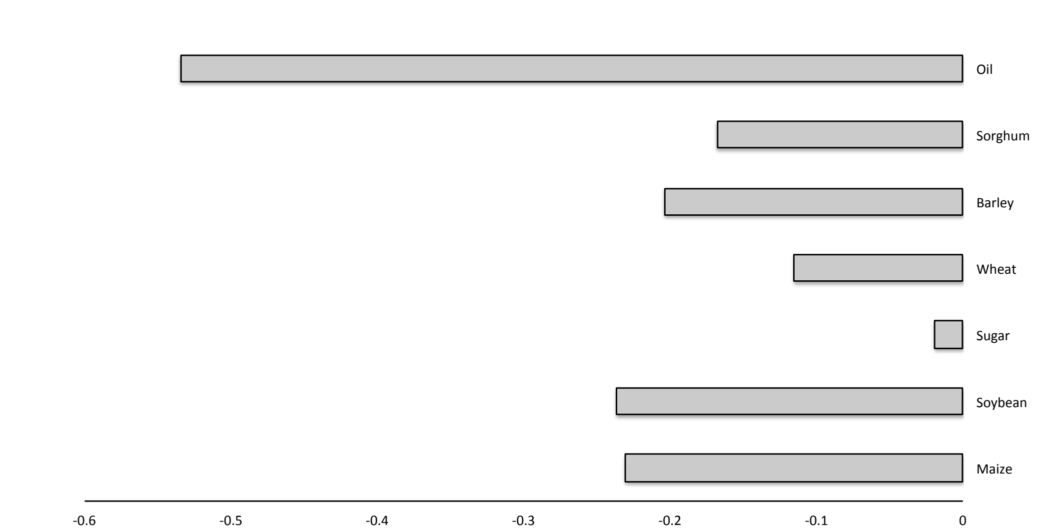
Overall, these results are consistent with our expectations. The first factor

[6]One important clarification from this analysis is that we cannot interpret the magnitude of the coefficients here presented nor can we draw a causal relationship. In order to make a definite statement on the causality of these factors we would have to impose over identifying restrictions on the system in order to isolate the structural components of each factor and factor loadings.

is associated with real global economic activity and fluctuations in the U.S. exchange rate relative to other currencies. On the other hand, the second factor highlights the relationship between the U.S. short term interest rate and market returns. Particularly, it exemplifies the nature of the relationship when the short-term interest rate is high the excess return on the market (e.g. foreign exchange, stocks, bonds, commodities, etc) appears to be low. This common factor describes two possible phenomena. One possible explanation is that it shows the trade-off (risk) between holding cash or assets and the other is that it measures an optimistic expectations on the assets being held will be matched with a higher return in future (e.g. speculative behaviour). Given the counter cyclical behaviour of this factor to the macroeconomic factor, it appears that the former hypothesis is what is being captured in these results. On the other hand, the third factor appears to be capturing the relationship between commodity prices with changes in inflation and market returns. This third relationship is consistent with the interest in investment in commodity futures indices as hedging positions against inflation pressures. Figures 4-4-4-6 show the cross correlation of each factor with the individual commodity price return in the portfolio. Figure 4-4 for example, shows how fluctuations in the first factor associated with macroeconomic fluctuations is associated with negative returns with the individual commodities. This is particularly evident crude oil , maize and soybeans. On the other hand Figures 4-5 and Figure 4-6 show the same relationship, but this time with respect to factors second and third factors. In this case, the positive correlation between the return to these commodity prices and the factors emphasize the hedging characteristics of commodity markets agains fluctuations in the macroeconomy.

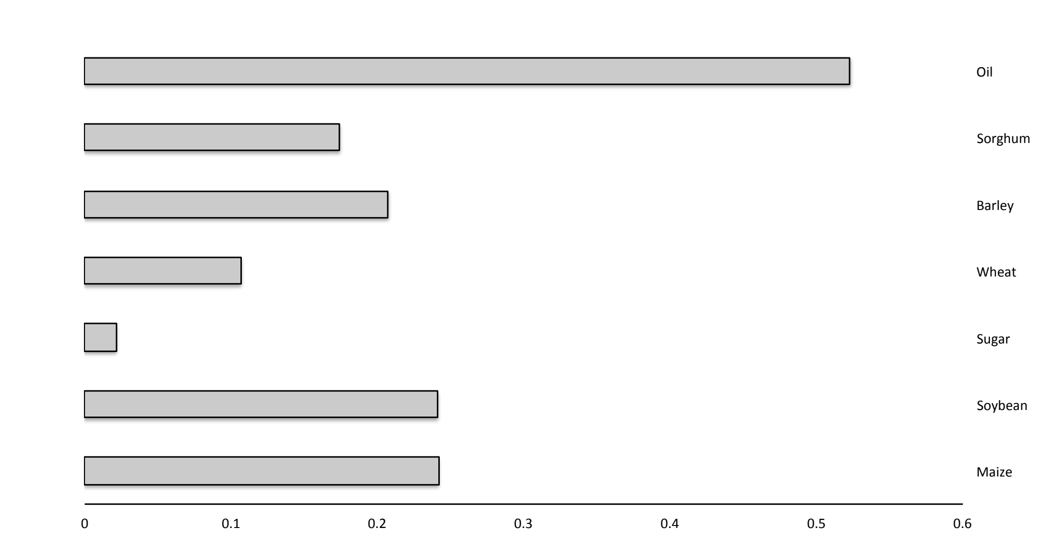
These results indicate a significant difference in the behaviour of our factors before 2000 and after this period (Figure 4-3). All evidence provided, suggests

Figure 4-4: *Factor 1 Loadings Correlation and Commodities*



	Maize	Soybean	Sugar	Wheat	Barley	Sorghum	Oil
Factor 1	-0.2304	-0.2364	-0.0192	-0.1151	-0.2036	-0.1678	-0.5342

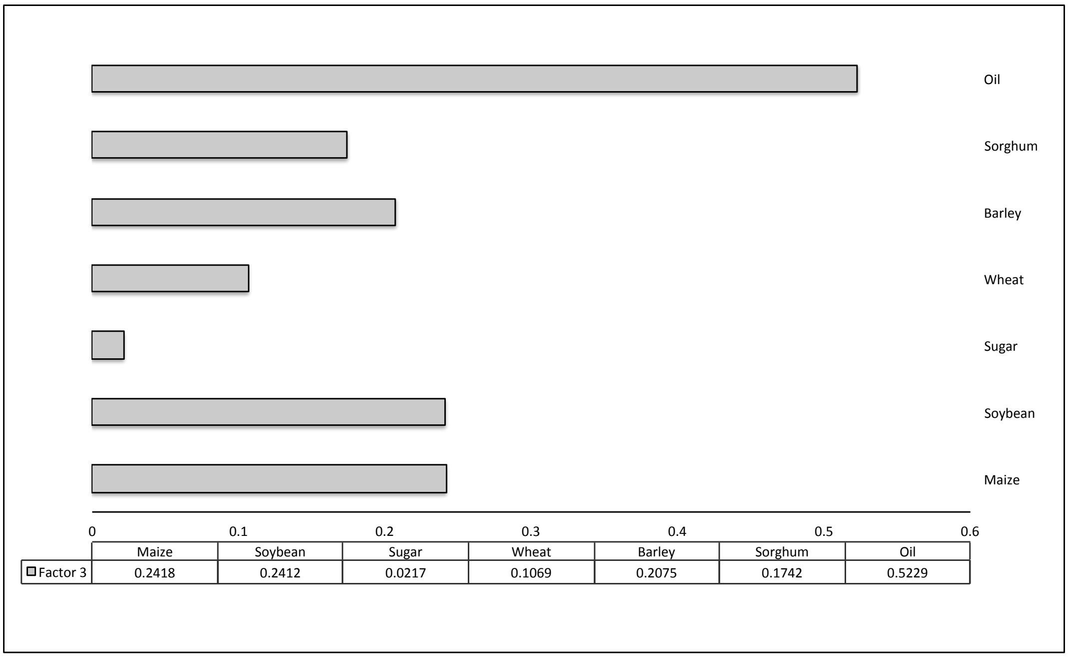
Figure 4-5: *Factor 2 Loadings Correlation and Commodities*



	Maize	Soybean	Sugar	Wheat	Barley	Sorghum	Oil
Factor 3	0.2418	0.2412	0.0217	0.1069	0.2075	0.1742	0.5229

that there is a substantial increase in the risk premium of the estimated factors with respect to the covariance of our commodity portfolio. Additionally, our results are consistent with that in the literature that there is weak evidence on the

Figure 4-6: *Factor 3 Loadings Correlation and Commodities*



speculative behaviour of investors in the commodity markets. On the other hand, these results indicate that a substantial proportion of our commodity portfolio covariance is due to common factors derived from fundamental or macroeconomic forces. Moreover, the second and third factors we are able to capture hedging positions against market forces and inflation. Moreover, the evidence from the empirical results provides strong evidence suggesting that futures commodity price indices are associated hedging positions against inflation and low market returns rather than speculative positions in the market.

4.5 Conclusion

In this study I have used arbitrage pricing theory in order to determine if there exists common components to the return of a portfolio of commodity prices. We begin our analysis from the theoretical assumption that positive shocks in the market are expected to have the same positive effect on individual stocks. Moreover, we expect that the individual stock's return has a completely idiosyncratic dynamic or belong to asset specific realized returns. Consequently, by holding a portfolio of commodities, a particular investor should be able to diversify the idiosyncratic risks and the assets, as a whole, should not contain any price risk. Therefore, we concentrate our analysis on the asset's covariance with only the common components ("factors"). These factors, are empirically estimated using a reduced rank regression approach.

For our analysis we use a portfolio of agricultural commodities and crude oil price returns with a monthly frequency from 1982 to 2013. For our risk factors, we incorporate a series of macroeconomic and market specific variables with the same frequency and covering the same period. The results indicate that among the macroeconomic variables and market related variables there are three factors associated with our portfolio of commodities covering approximately 90% of the covariate of our portfolio return. The first factor has been identified as that associated with macroeconomic variables, while the second and third factors are associated with hedging positions from investors. These results indicate that contrary to a number of studies in the literature, our results suggest that it is not speculation driving the return prices during this period. On the other hand, our results appear to show that future commodity price indices, as argued, serve as hedging tools for investors when facing inflationary and upward pressure in commodity prices.

CHAPTER 5 CONCLUSION

This thesis has studied the extent to which macroeconomic factors, crude oil prices and the financialization of commodity markets have contributed to fluctuations and price formation of a number of global agricultural commodity prices. Overall, this work contributes to the current body of literature by providing a comprehensive analysis of the means as well as volatility of these dynamics. In addition, this work provides insights into the extent to which futures commodity markets impact speculation in the spot market.

The current body of literature is not consistent in its findings with respect to the long-run effects of crude oil prices on food commodity prices. Moreover, it lacks a study that incorporates and simultaneously models demand side factors into the the dynamics. The current state of the literature relies on models that have model this relationship in a bi-variate fashion without incorporating important determinants of commodity prices such as aggregate demand, inflation, exchange rates and interest rates. On the other hand, in the short-run and volatility analysis the literature is also exhausted with bivariate models that do not offer a definite answer to the fluctuations seen in the agricultural commodity markets. With this information in mind, I attempt to model the long and short-run dynamics of these commodities and attempt to offer an alternative and comprehensive analysis of the factors driving these commodities.

In the first part of this thesis I analyzed the long-run relationship between the real world price of maize, soybeans and maize with the real world price of crude oil and a series of global macroeconomic variables. In this work I have employed a cointegration VAR analysis using monthly series from January 1982 until December 2012. The main results indicate a strong relationship between fundamentals and the world price of Maize and Soybeans during this time period. More precisely, I document significant causal long-run relationships between these agricultural commodities with the real world price of crude oil, the real interest rate and the real U.S. exchange rate. Additionally, this study shows that in the long-run crude oil prices and these agricultural commodities share a one-to-one relationship. That is, a one-percent increase in the price of real crude oil has is associated with a one-percent increase in the price of maize and soybeans. Despite the literature suggesting the neutrality between agricultural commodities and energy prices (mainly crude oil) our findings show that a strong long-run causal relationship between these factors and macroeconomic factors. Moreover, this work concludes that permanent shocks to crude oil prices are transmitted to both maize and soybeans by a factor of 0.67 for both commodities. Consequently, these results contradicts the results from Campiche et al. [2007], Yu et al. [2006], Zhang et al. [2009, 2010] where no long-run (or partial) relationship was found between these variables. In addition, our results show that despite the instability associated with the period between 2007/08, the long-run relationship between crude oil and these agricultural commodities has remained stable during the entire sample period. This results contradicts those found in studies by Ciaian and Kancs [2011a,b], Harri et al. [2009], Natanelov et al. [2011] where instabilities in individual variables are used to model instability in the cointegrating space. Our findings suggests that despite the period of instability between 2007/08, the long-run estimated coefficients are stable along the sample period. The only period of instability associated with these relationships is during the peak of the commodity shock and financial crisis of 2007/08, which provides some evidence confirming the findings by Tang and Xiong [2012a] and Pen and Sevi [2013] that speculation might have played an important role in explaining some of the price increases during this period. Finally, the results from the MA analysis supports the finding that although the real interest rate and the U.S. exchange rate are cointegrated with these commodities, it's only permanent shocks to real crude oil prices that have a permanent effect on the commodity price behavior. Therefore, from this study I conclude that fundamentals are (in particular demand factors) the crucial determinants of the long-run dynamics of both these two agricultural food commodities. In particular, crude oil prices are an important determinant of the long-run price adjustments of these commodities and the natural extension of this study is to analyze this relationship using volatility models with both a univariate and multivariate approach.

This piece of research implies that there exists no neutrality between these agricultural commodity prices and the world crude oil prices. This has a profound implication for nations whose share of food is high relative to their income. This is mainly the case of developing nations around the world and particularly those net importers of corn and soybeans (and its derivatives). This implies that policies designed to stabilize these commodities need to consider the link between world oil and commodity prices here argued. Similarly, permanent policy changes in the crude oil market need to be examined closely by both net exporter and importer of these commodities in order to accommodate appropriate macroeconomic stabilization policies. Additionally, for those countries affected by food inflation policy makers need to pay close attention to developments in the global energy markets in addition to the traditional demand and supply channels. For example, fluctuations in the U.S. dollar exchange rate are found to explain a significant variation in the long-run of these commodity prices as well as the short-term interest rate. All these factors need to be considered when designing appropriate response to commodity price fluctuations. An additional line of research would be to understand the impact of these dynamics in countries given their individual characteristics and positions in the world energy and commodity markets (net exporters or importers of energy and food commodities). These results consider the global impact, but do not account for individual heterogeneity of countries when it comes to their ability to absorb shocks in both energy and agricultural markets. An apparent extension of this work would be to understand these dynamics at a country-specific level.

In the second empirical chapter I have analyzed the degree of interdependence between a number of world agricultural commodities with the crude oil market and three global macroeconomic factors. The aim here was to establish the level at which volatility in the energy market and instability of global macroeconomic factors are related to these agricultural commodity markets. This is a an extension of the first empirical chapter, but also in response to an effort of improving the current understanding of the consequences from the recent commodity price shock and the claims of a strengthening relationship between energy and commodity markets. The aim of this study is to offer a deeper understanding of the channels through which global food prices are affected and offer an adequate policy response. To accomplish this, I have applied a VAR-cDCC-MGARCH model to determine the degree of interdependence among these markets from 1982 to 2012 and analyze the stability of this relationship across the sample period.

Overall, the results from this study indicate that the volatility interdependencies between these factors cannot be explained by the crude oil price returns and macroeconomic factors. Therefore, I am not able to establish any interdependence between maize price returns with crude oil prices and macroeconomic factors. This study also shows that even though the soybeans price return presents a negative and statistically significant relationship with the U.S. exchange rate return, it is a very weak relationship. Nevertheless, these results indicate that this relationship is not constant over time and there is evidence of asymmetry during these periods of macroeconomic instability. Similarly, sugar price returns do not present any evidence of being linked with crude oil price returns and any of the macroeconomic factors except the Kilian index of global economic activity. Thus, I conclude that the observed price instability leading to the commodity price shock of 2006-08 is not associated with volatility in the energy or demand-side factors. Thus, the results indicate that in these global agricultural markets the volatility appears to be associated with the financialization of commodities. The results presented disagree with those found by Manera et al. [2013] and are in line with a number of studies already in the literature such as Gilbert [2010], Irwin and Sanders [2011], Du et al. [2011], Hailu and Weersink [2011], Tang and Xiong [2012a], Pen and Sevi [2013],Ajuzie [2013],Williams [2014], Gilbert and Pfuderer [2014] , Gilbert [2015]. Consequently, from a policy perspective, our results indicate that in order to reduce future agricultural market volatility it is important to create and develope efficient market monitoring mechanisms. On the other hand, the results from the cDCC model show that crude oil price returns are closely linked to fluctuations in monetary and global macroeconomic policies. Specifically, the results show that crude oil price returns are associated with the U.S. exchange rate and the Kilian index to a lesser extent and present a strong volatility correlation with the interest rate of U.S. three month treasury bills. These results also confirm the findings of a number of recent studies. For example, Schryder and Peersman [2013] show that changes in the U.S. dollar exchange rate are an important determinant of the volatility of the global price of crude oil, die to its influence on oil demand. This is because all commodities are priced in U.S. dollars and consequently it acts as the primary channel through which monetary shocks are propagated through the market. Also, Fattouh et al. [2013] and Knittel and Pindyck [2013] show that economic fundamentals have been the main drivers of volatility in the global oil markets. Similarly, these results also show the importance of monetary policy (interest rates) in determining fluctuations in the global oil market, which also coincides with the findings of Frankel [2008]. That is, as interest rates increase, crude oil becomes less attractive as an asset for investors in addition to the fact that the main aim of contractionary monetary policy is to decrease overall demand including that of crude oil. Consequently, positive shocks in the global oil market force central banks to increase interests rate in order to counteract inflationary pressures and thus contributes to a decline in economic activity.

One of the main conclusion from this study is that despite the fact that volatility in global agricultural commodity prices has been argued to be linked to a strengthening relationship with energy markets, our results do not support this argument. This result suggests that these commodities suffer from different set of market information that is not related to energy markets. Therefore, crude oil and macroeconomic variables are unable to explain the behaviour of these commodities volatility and consequently should be viewed as exogenous. On the other hand, the dynamic correlations between the price returns of maize and soybeans present a significant correlation across the entire period. This co-movement is consistent with the concept that commodities alike are affected by similar market shocks and in particular during periods of price increases such as the 2007-08 commodity boom. The increase in the interdependence among these commodities is important in the argument of their use in the biofuel industry and more work to understand its interaction is needed to capture any causal relationship.

Moreover, this study established that global macroeconomic factors cannot entirely explain the observed volatility in global agricultural commodity markets. Therefore, there is a level of excessive volatility in these agricultural commodity prices that cannot be explained by the traditional channels of demand and supply. On the other hand, fluctuations in the global crude oil prices are fundamentally explained by global macroeconomic factors which is in line with recent developments in the literature. Moreover, the study shows that the there exists a string and significant relationship between the returns to the futures commodity price index and all the commodities analyzed including crude oil. These results, support the view that a substantial source of the volatility in agricultural commodities, not captured by our model. One source of the short-run driving forces might be embedded in the fluctuations of inventories of these commodities as predicted by the theory. On the other hand, an additional source of the unexplained volatility might be due to the financialization of these commodities and speculative behavior in the market for commodities. In an effort to address this questions, I show that there is strong and significant conditional correlation between the return on commodity index investment and the commodity markets analyzed. However, as far as to claim that there exists a causal link is beyond the scope our methodology and ultimately an empirical question to address. Nevertheless, there is a need to understand the cross-market dependencies and driving factors of these price returns under the growing financial influence in commodity markets. Therefore, given the results here presented, a natural extension of our work is to determine the extent to which the financialization of these agricultural commodities is responsible for the observed volatility in these markets.

In the third empirical chapter I have used arbitrage pricing theory in order to empirically estimate common components to the return of a portfolio of commodity prices with respect to a set of macroeconomic and financial market indicators. Specifically, I construct a portfolio of commodities using a monthly price series from January 1982 to December 2013 for six agricultural commodity price series (e.g. maize, soybean, sugar, wheat, barley and sorghum) and crude oil prices. The common factors have been extracted from a set of global macroeconomic variables such as the weighted U.S. dollar exchange rate and three-month Treasury bill secondary market rate, the U.S. Industrial Production and an index for the real global economic activity. Furthermore, in an effort to capture the extent to which the financialization of commodities contributed to the risk premium of spot commodity prices I also include the Goldman Sachs Commodity Index (S&P GSCI) and the excess return on the market.

Since I am interested in estimating the common components which are important factors in determining commodity price returns, I use a reduced rank regression to estimate these factors in order to concentrate the analysis on the asset's covariance as opposed to the variance (e.g. PCA). One of the main results from this study is that the factor which explains approximately 66% of the covariance in the commodity portfolio is associated with the macroeconomic variables. Furthermore, the second and third factors are those associated with market specific factors and investment in the commodity futures market, which explains about 25% of the covariance (for a total of about 91% among all three factors). The first factor has been identified as that associated with macroeconomic variables, while the second and third factors are associated with hedging positions from investors against inflationary pressures. These results indicate that contrary to a number of papers in the literature, it is not speculation driving the return prices during this period. On the other hand, our results appear to show that future commodity price indices, serve as hedging tools for investors when facing inflationary and upward pressure in commodity prices. This results also have an important implication with the conclusion of the second empirical work here presented. In that sense, these results imply that the volatility not captured by the macroeconomic variables in the cDCC model might find origin in commodity or market specific sources which is in line with the theory of commodity storage.

There are important policy implications we can derive from this thesis. It suggests that accommodative monetary policy (particularly that conducted by the U.S. during the early 2000s) although it is effective in stimulating economic recovery from periods of sluggish economic growth, it can be trigger for commodity price inflations such as that seen during the 2006-08 period. Also, since there is a long-run homogeneity (one-to-one) relationship between the real price of crude oil and real price of maize and soybeans, countries that depend on the imports (or exports) of these commodities can develop stabilization policies by taking into consideration the spillover effects from energy markets to agricultural commodity markets. Moreover, I have shown that investors can reduce their exposure of risks exposure from global macroeconomic shocks by investing in commodity price futures indices.

I would like to conclude by outlining the limitations of this study and providing a number of points that deserve close attention and further research. The first limitation, at least concerning the first empirical study, is that the parameters estimated in the cointegrated VAR model are linear. This is a significant limitations since we know that the effects increasing oil prices on the economy as a whole are much different that negative price shocks. Similarly, we have seen from the commodity price series that positive price shocks are more pronounced and frequent than negative commodity shocks. Therefore, further research on the non-linear relationship among these variables would offer more insights into the dynamics and long-run relationship between these variables. Additionally, the variables used in this study are in reduced form and the price of oil changes from both discovery of new oil fields (supply side) as well as changes in consumer income (demand side). These changes are likely to have different effects in commodity price dynamics and alternative modelling approaches to the ones used here can be used to enhance the understanding of its implications. Thus, the literature would benefit from further empirical research using structural models such as that by Baumeister and Kilian [2013] that can isolate demand from supply shocks and its individual effects on commodity price dynamics. Furthermore, from the conclusions of the cDCC model, there is no evidence that macroeconomic and crude oil prices affect the price volatility of these commodities. Failure to capture any comovement in the price volatility across these variables indicates that the source of this short-run dynamic is due to market specific shocks and greater improvements can be made by including structural considerations such as inventory stockouts. Consequently, this results and the literature on price volatility of commodities would be enhanced by including further studies that include this information in the information set.

Finally, with respect to the effects of the financialization of commodity markets and their possible effects in the volatility of commodity prices I have only considered market oriented factors in addition to the commodity futures index. This is because the literature has extensively documented the effects of sources of the most recent commodity price boom through the demand from China and other emerging markets in connection with a stagnant commodity supply. Furthermore, even though I have been able to estimate and identify the factors by their components it is difficult to draw a causal relationship among these. Therefore, there exists the need to develop empirical studies that can directly determine if trading behaviour in the futures price changes have a causal link to developments in the spot markets and more importantly determine the directional of the causality. Thus, studies that can apply clear identification strategies that can test the hypotheses or any evidence of the impact of trading behaviour in futures commodity markets feeds into the spot market.

APPENDIX A

Table A.1: *Univariate ARMA (p, q) Selection*

		ARMA(1,0)	ARMA(2,0)	ARMA(3,0)	ARMA(0,1)	ARMA(0,2)	ARMA(0,3)	ARMA(1,1)	ARMA(1,2)	ARMA(1,3)	ARMA(2,1)	ARMA(3,1)	ARMA(2,2)	Min. Inf.Crit.
Maize (2,1)	**Akaike info Criterion**	-2.954	-2.947	-2.939	-2.954	-2.951	-2.948	-2.949	-2.944	-2.940	**-2.966**	-2.960	-2.962	-2.966
	Schwarz Criterion	**-2.933**	-2.915	-2.896	-2.933	-2.919	-2.906	-2.917	-2.901	-2.887	-2.923	-2.907	-2.909	-2.933
	Hannan-Quinn Criterion	-2.946	-2.934	-2.922	-2.946	-2.938	-2.931	-2.936	-2.927	-2.919	**-2.949**	-2.939	-2.941	-2.949
Soyb (2,1)	**Akaike info Criterion**	-3.015	-3.013	-3.011	-3.019	-3.018	-3.019	-3.014	-3.016	-3.013	**-3.024**	-3.007	-3.012	-3.024
	Schwarz Criterion	-2.994	-2.981	-2.969	**-2.998**	-2.986	-2.977	-2.982	-2.974	-2.960	-2.981	-2.954	-2.959	-2.998
	Hannan-Quinn Criterion	-3.007	-3.000	-2.994	**-3.010**	-3.005	-3.002	-3.001	-2.999	-2.992	-3.007	-2.986	-2.991	-3.010
Sug (1,2)	**Akaike info Criterion**	-1.837	-1.849	-1.846	-1.845	-1.840	-1.835	-1.840	**-1.857**	-1.852	-1.846	-1.855	-1.854	-1.857
	Schwarz Criterion	-1.816	-1.818	-1.804	**-1.824**	-1.808	-1.793	-1.808	-1.815	-1.800	-1.804	-1.802	-1.801	-1.824
	Hannan-Quinn Criterion	-1.829	-1.837	-1.829	-1.837	-1.827	-1.818	-1.827	**-1.840**	-1.831	-1.829	-1.834	-1.833	-1.840
Oil (1,2)	**Akaike info Criterion**	-2.327	-2.323	-2.318	-2.329	-2.323	-2.322	-2.325	**-2.321**	-2.319	-2.323	-2.318	-2.241	-2.329
	Schwarz Criterion	-2.306	-2.291	-2.276	**-2.307**	-2.291	-2.279	-2.293	-2.278	-2.266	-2.281	-2.265	-2.209	-2.307
	Hannan-Quinn Criterion	-2.318	-2.310	-2.301	**-2.320**	-2.311	-2.305	-2.313	-2.304	-2.298	-2.306	-2.297	-2.228	-2.320
MTB3 (3,1)	**Akaike info Criterion**	-6.397	-6.441	-6.470	-6.500	-6.599	-6.618	-6.629	-6.625	-6.611	-6.627	**-6.653**	-6.620	-6.653
	Schwarz Criterion	-6.375	-6.410	-6.427	-6.479	-6.567	-6.576	-6.597	-6.583	-6.558	-6.585	**-6.599**	-6.567	-6.599
	Hannan-Quinn Criterion	-6.388	-6.429	-6.453	-6.491	-6.586	-6.601	-6.616	-6.608	-6.590	-6.610	**-6.632**	-6.599	-6.632
LXR (3,1)	**Akaike info Criterion**	-5.998	-6.002	-6.000	-6.004	-5.999	-5.997	-6.004	-6.011	-6.006	-6.014	**-6.019**	-6.016	-6.019
	Schwarz Criterion	-5.977	-5.971	-5.957	**-5.983**	-5.967	-5.954	-5.973	-5.969	-5.953	-5.971	-5.966	-5.963	-5.983
	Hannan-Quinn Criterion	-5.990	-5.990	-5.983	-5.996	-5.986	-5.980	-5.992	-5.994	-5.985	-5.997	**-5.998**	-5.995	-5.998
Y (3,1)	**Akaike info Criterion**	-2.666	-2.734	-2.727	-2.721	-2.720	-2.729	-2.719	-2.733	-2.738	-2.730	**-2.739**	-2.593	-2.739
	Schwarz Criterion	-2.644	**-2.702**	-2.684	-2.700	-2.688	-2.686	-2.687	-2.680	-2.696	-2.687	-2.686	-2.562	-2.702
	Hannan-Quinn Criterion	-2.657	**-2.722**	-2.710	-2.713	-2.707	-2.712	-2.706	-2.712	-2.721	-2.713	-2.718	-2.581	-2.722

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